Quantifying System Reliability in Rail Transportation in an Aging Fleet Environment

by
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Declaration

By submitting this thesis electronically, I declare that the entirety of the work contained therein is my own, original work, that I am the authorship owner thereof (unless to the extent explicitly otherwise stated), and that I have not previously, in its entirety or in part, submitted it for obtaining any qualification.

24 February 2015

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Abstract

In recent years, the management of physical assets has become increasingly important, even more so, in asset intensive organisations. This research work presents an overall approach to quantify reliability of rolling stock assets in the rail environment. The current maintenance management system in the case studied is over-reliant on cancellations and delays as reliability measure. The objectives of this study were, therefore, to develop a scientific approach to quantify the reliability of the rolling stock fleet and to develop a maintenance planning model based on system reliability. The research methodology followed made use of failure statistics, failure distributions and the interdependence of different systems to determine the impact of component failures on the overall system reliability. This could then be used to determine the reliability of individual train sets in order to better understand their performance. The reliability measure could be used for predicting component and train set failures as well as to better understand the contribution of maintenance towards reliability, hence the term Reliability Based Maintenance. The model, validated with real data, illustrates how the reliability measure can be used to determine maintenance intervals of different train sets. Based on the results, recommendations are made in relation to future planning of the maintenance strategy.

Opsomming

Die bestuur van fisiese bates het in die afgelope tyd meer belangrik geword, veral in organisasies wat afhanklik is van hulle fisiese bates. Hierdie navorsing stel ‘n metode voor wat die betroubaarheid van rollende materiaal bates in die spoor bedryf kwantifiseer deur gebruik te maak van falingstatistiek. In die huidige instandhouding bestuurstelsel van die gevallestudie word daar te veel gesteun op kansellasies en vertragings van treine as ‘n betroubaarheids meting. Daarom was die doelwitte van die navorsing om ‘n wetenskaplike benadering te ontwikkel om betroubaarheid van rollende materiaal the kwantifiseer, en om ‘n instandhouding beplannings model voor te stel, gebaseer op sisteem betroubaarheid. Die navorsingsmetodologie is gebaseer op falingstatistieke, falingverspreidings, en die interafhanklikheid van stelsels word gebruik om die invloed van komponent falings op die betroubaarheid van die totale stelsel te bepaal. Hierdie benadering word dan gebruik om die betroubaarheid van individuele treinstelle en die werksverrigting van individuele trainstelle te bepaal. Hierdie instandhouding meting kan gebruik word om falings van komponente en treinstelle te voorspel, asook om die bydrae van instandhouding tot betroubaarheid beter te verstaan, daarom genoem Betroubaarheids Gebaseerde Instandhouding. Dit is ook geïllustreer hoe die betroubaarheid meting gebruik kan word om instandhouding intervalle te bepaal. Die betroubaarheid model is met werklike data gevalideer en aanbevelings word gemaak hoe om betroubaarheid te gebruik om die toekomstige beplanning van instandhouding te doen.

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Glossary

AM	- Asset Management
AMSAA	- Army Material Systems Analysis Activity
A-Shed	- Passenger Safety and Comfort (PS&C) maintenance intervention
B-Shed	- Intermediate maintenance intervention
CMMS	- Computerised Maintenance Management System
COMP	- Compressor
CV	- Coefficient of Variation
C-Shed	- Full maintenance intervention
DOM	- Design Out Maintenance
ERS	- Enterprise Resource System
EXH	- Vacuum Exhauster
FMEA	- Failure Mode and Effects Analysis
FMECA	- Failure Mode and Effects and Criticality Analysis
FMMS	- Facility Maintenance Management System
FOM	- Force of Mortality
FS	- Failure State
GO	- General Overhaul
GQL	- General Query Language
HPP	- Homogeneous Poisson Process
i.i.d.	- Independent and identically distributed
ISO	- International Organisation for Standardisation
KS	- Kolmogorov-Smirnov
L-R	- Lewis-Robinson
LSE	- Least Squares Estimation
LTT	- Laplace Trend Test
MC	- Motor Coach
MDT	- Mean Down Time
MK	- Mann-Kendall
MLE	- Maximum Likelihood Estimation
MS	- Maintenance State
MTBF	- Mean Time Between Failures
MUT	- Mean Up Time
NHPP	- Non Homogeneous Poisson Process
OS	- Operating State
PAM	- Physical Asset Management
PdM	- Predictive Maintenance

PM	- Preventative Maintenance
PMRI	- Preventative Maintenance, Replacements and Inspections
PRASA	- Passenger Rail Agency of South Africa
PS&C	- Passenger Safety and Comfort
PT	- Passenger Trailer
R&R	- Remove and Replace
RAMS	- Reliability, Availability, Maintainability and Safety
RBD	- Reliability Block Diagram
RBM	- Reliability Based Maintenance
RCM	- Reliability Centered Maintenance
ROCOF	- Rate of Occurrence of Failures
RP	- Renewal Process
RSR	- Railway Safety Regulator
RTF	- Run-To-Failure
SQL	- Structured Query Language
SUPPLY	- 110V Supply Set
TDM	- Time Directed Maintenance
TM	- Traction Motor
TPM	- Total Productive Maintenance
MIL-STD	- United States of America Department of Defence Military Standard

Nomenclature and Greek Symbols

☺	- Improving or "happy" system
☹	- Deteriorating or "sad" system
α	- Confidence level
α_0, α_1	- Variables used in the log linear NHPP
β	- Weibull shape parameter, variable used in the power law NHPP
D1	- New, or good as new, used in Figure 2.4
D2	- Minor deterioration stage, used in Figure 2.4
D3	- Major deterioration stage, used in Figure 2.4
D_n	- KS test statistic
E	- Expected number of failures
e_i	- Errors used in the LSE
F	- Unreliability of a system
$f(x)$	- Failure density
$F(x)$	- Cumulative Failure Distribution
$F_0(x)$	- hypothetical cumulative distribution function used in the KS test
F_i	- Unreliability of an individual unit in a system
η	- Weibull characteristic life
H_0	- Null Hypothesis
λ	- Constant FOM used in the exponential distribution, Variable used in the power law NHPP
N	- Total number of units in a system
ρ	- Constant ROCOF used in the HPP
$\rho(t)$	- Time variant ROCOF used in the NHPP
$\rho_2(t)$	- Power law NHPP
$\rho_1(t)$	- Log-linear NHPP
R	- Reliability of a system
$R(x)$	- Survival Function
R_i	- Reliability of an individual unit of a system
S	- Mann-Kendall test statistic
$S_n(x)$	- Cumulative step-function of a population used in the KS test
T	- Continuous global time
T_n	- Arrival times of events
U_L	- Laplace Trend Test value
U_{LR}	- Lewis-Robinson Trend Test value
X_n	- Inter-arrival times of events
$\overline{X}$	- Mean
z_α	- Cumulative Distribution value, based on α
$z(x)$	- Hazard Function

1 INTRODUCTION

An effective rail system depends on the seamless integration of a number of complex systems, thus, if one system fails, the service can be severely affected. Reliability, availability, maintainability and safety (RAMS) are seen as major contributors to the quality of service. These are well covered and adapted for railways in the British Standard European Norm (BS EN) 50126 [1]. The standard recognises that railway safety and availability are inter linked (Figure 1.1) and regards them as the most important elements. As such, railway safety and availability can only be achieved if all the reliability and maintainability requirements are achieved. The quality of railway service is not only influenced by the four elements, RAMS, but also by operations, maintenance and other factors as shown in Figure 1.1.

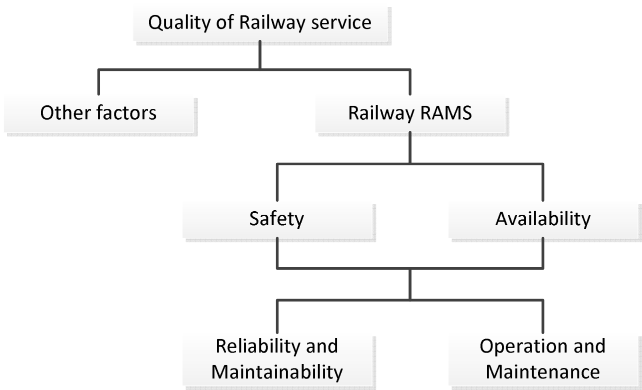


Figure 1.1: Factors contributing to the quality of railway service [1]

While all the elements of RAMS are important in the management of physical assets, the focus of this study will be on quantifying the reliability of railway rolling stock and the application of reliability techniques in order to define a forward looking and leading reliability measure. A case study method is employed, using data from a South African rail operator, Metrorail, a subsidiary of PRASA (Passenger Rail Agency of South Africa). Metrorail operates an aging rolling stock fleet making predominant use of Condition Based Maintenance (CBM) during predetermined maintenance inspection intervals.

1.1 Research Problem

The benefits of an effective maintenance strategy and maintenance techniques can only be seen after being implemented for a period of time. In a study by Huisman et al [2] of the Netherlands Railways, rolling stock management is classified as a strategic planning process with a time horizon of between 10 to 20 years. This indicates that the maintenance strategy and techniques must be carefully selected because incorrect maintenance techniques can have a detrimental effect on the effectiveness of the business in the long term.

Observations at Metrorail led to the formulation of the research objectives, which were identified around the selection of the most appropriate maintenance technique. In 2009, Metrorail acknowledged that maintenance of train sets was not effective, with many wasteful activities related to over maintaining. Metrorail adopted CBM as a maintenance technique [3]. This meant that instead of the periodic replacement of components irrespective of condition, components would only be replaced after a condition assessment has been done. The frequency of maintenance interventions remained unchanged at two weeks, but the focus of maintenance shifted. The problem associated with CBM is that the *condition* is normally classified based on the visual condition of the mechanical and/or electrical systems and performance measurements from metrology. Consequently, non-condition related failures (e.g. *swelling* of interpole coils in a traction motor) cannot be entirely prevented using CBM. Also, CBM cannot be used in isolation and across the board for all systems. Therefore, other techniques to quantify system reliability in rail transportation, especially in an aging fleet environment, are required.

1.2 Research Objectives

At Metrorail, one of the shortcomings in the maintenance management system of the current rolling stock fleet, is the over reliance on cancellations and delays as a reliability measure. Cancellations and/or delays cannot be directly linked to the source of unreliability, and can therefore not be effectively used in the planning of maintenance. This investigation, thus, seeks to quantify system reliability in rail transportation, especially in an aging fleet environment.

Based on the shortcomings of the application of the definition of reliability, the primary objective of this research is:

a) To develop a scientific approach to quantify the reliability of the rolling stock fleet, in lieu of cancelations and delays.

The frequency of maintenance is questioned, specifically, the waste due to over maintaining, and whether a more scientific approach can be found to determine the optimum maintenance interval. This lead to the secondary objective, which is:

b) To develop a maintenance planning model for railway rolling stock based on system reliability.

1.3 Research Design and Methodology

This investigation seeks to develop a model to quantify system reliability in rail transportation in an aging fleet environment. The methodology, described in detail in chapter three, is summarised below:

- A comprehensive literature review on reliability and the advances of reliability thinking is done to illustrate the context of reliability in Asset Management.
- Based on the literature review, a reliability model for rolling stock in the rail environment is developed based on the configuration of the current fleet of trains from Metrorail.
- Using statistical techniques and analysis of failure data obtained from the case study, the model is applied to satisfy the research objectives.
- The application of the model is discussed.

1.4 Outline of Research

This study is divided into six chapters. A brief description of each chapter is given below:

Chapter 1 provides background and the rationale for the research.

Chapter 2 introduces the general concepts of reliability, discusses techniques used in the application of reliability in engineering assets as well as how data can be manipulated and interpreted for use in reliability analysis, hereafter called a Reliability Based Maintenance (RBM) model.

Chapter 3 explains the methodology followed to apply the literature research in a case study.

Chapter 4 shows the application of the RBM model in a case study. Reliability in the rail context is discussed where after, the maintenance strategies and techniques of Metrorail are discussed. Through the remainder of the chapter, the application of the RBM model at Metrorail as a case study is discussed.

Chapter 5 discusses the results and the potential areas of application.

Chapter 6 concludes the research, discusses limitations of the study and proposes direction for future research work.

2 LITERATURE REVIEW

Chapter one provided the background to the study, the problem statement as well as the objectives of this study. This chapter introduces the theory on reliability, the importance thereof and the theory behind quantifying reliability. The literature review is divided in three parts starting with the broader context of reliability in the asset management context, maintenance strategies and maintenance techniques. In the last part, the modelling of reliability is discussed as well as the various statistical techniques and methods used to quantify reliability.

2.1 Asset Management System

In the last couple of years, the management of physical assets has become increasingly important. A framework for Physical Asset Management (PAM) was defined by the Institute of Asset Management in 2004 and officially released as an Asset Management International Organisation for Standardisation (AM ISO) standard in January 2014. The standard is applicable to any organisation where physical assets are critical for organisational success. There are two main parts applicable to Asset Management (AM), defined as an object ("engineering asset") and a process of managing that asset [4].

An asset is defined in the Oxford English Dictionary as "all the property of a person or company which may be made liable for the payment of debts" [5]. The key concepts of this definition are that (a) a value is attributed to (b) property by (c) a person or company. Thus, an asset is more than just a physical object but is seen as an object with value.

An asset can be defined more specifically in the context of AM as an "engineering asset", which provides the means for the realisation of value. Amadi-Echendu et al [4] differentiate between "engineering" asset objects and "financial" asset objects. They give examples of financial asset objects such as patent rights, trademarks, securities traded on stock exchanges and derivative securities of various sorts, which exist only as contracts between legal entities. Engineering objects, which can include land and buildings, inventories, equipment, vehicles and equipment, exist independently of any contract and are managed by engineering asset managers. Accountants and economists refer to these assets as "real assets" [4]. Figure 2.1 shows the relation between financial and engineering assets, where the latter can be linked to the base of a pyramid on which the other assets rest.

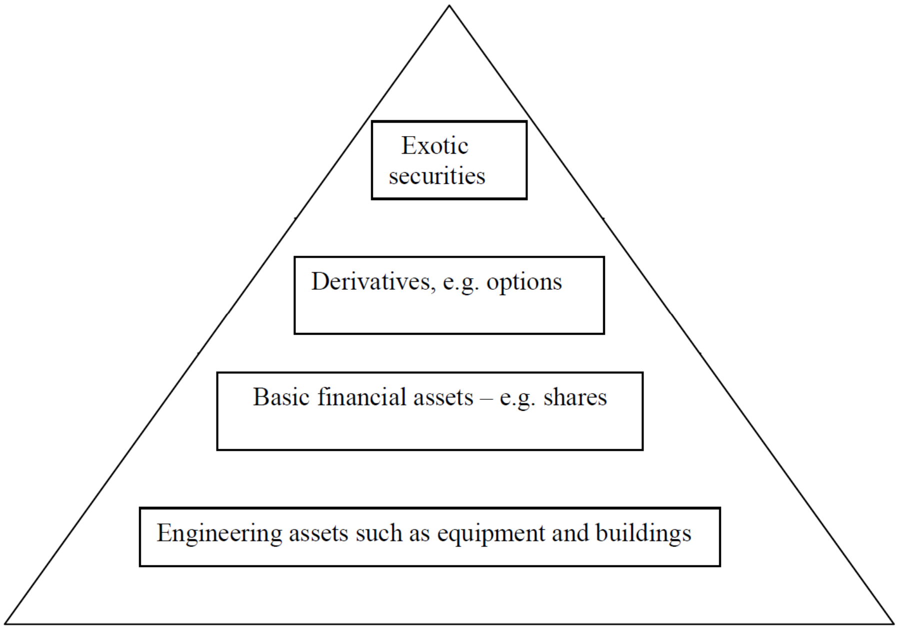


Figure 2.1: Fundamental nature of engineering assets [4]

AM is defined by ISO 55000 [6] as "coordinated activities of an organisation to realise value from assets". It combines all activities necessary to ensure that an engineering asset provides the means for the realisation of value and recognise that all asset types are interdependent. The optimal management of engineering assets also involves the management of other assets like information assets, human assets, financial assets and other intangible assets, therefore, removing the traditional "silos" between different functions.

The emphasis on effective AM processes can be seen in Figure 2.2, where the asset itself is only a single block in the bottom triangle, and the processes make up the rest of the figure. It can be seen in Figure 2.2 that the organisation strategic plan and the AM objectives and strategies are aligned through the AM policy by setting the AM commitments [7]. As such, continual improvement drives the sustainability of the AM system and the complete life cycle of the asset.

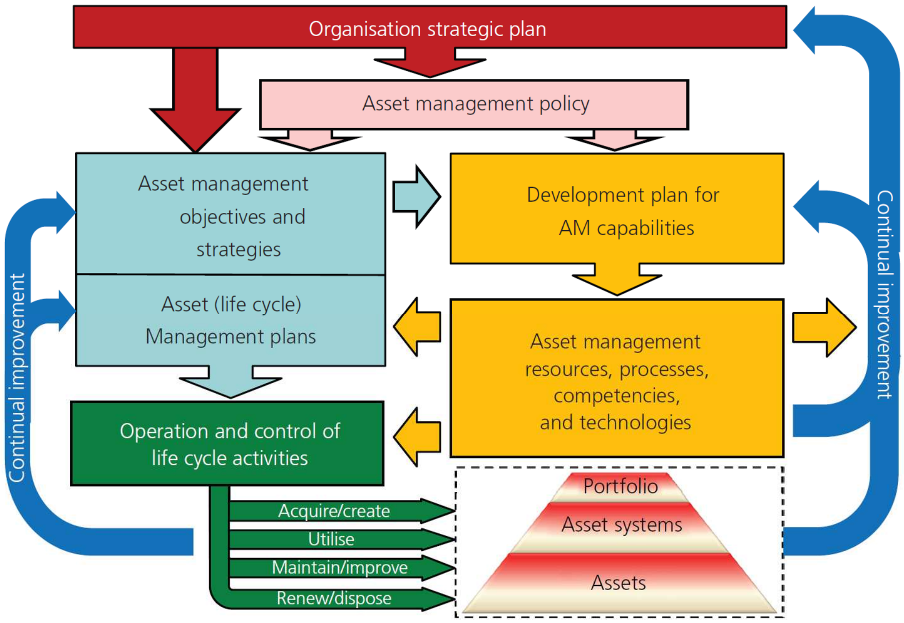


Figure 2.2: ISO55001 elements of an Asset Management system [7]

The AM ISO standards, published as the 55000 family of standards, contain the *requirements* of an AM system but do not specify the design of the system. The context of the AM system is shown in the bottom part of Figure 2.2, which lists the typical considerations applicable to each level of AM, from the corporate/organisation management level down to the individual asset.

The focus of this study will be on the bottom elements of Figure 2.2, i.e. activities around the management of individual assets over their life cycles. The remainder of this study will be focussed on physical assets, and the term "engineering asset" will be used selectively.

2.1.1 Definition of Reliability

The word reliability developed from the word rely, which is defined as a "sense of dependence or trust and perhaps has a notion to fall back on" [8]. It was first used as early as 1816 by the poet Samuel T Coleridge, who wrote about his friend who inspired everybody around him with "perfect consistency and absolute reliability" [9]. Since then, the concept of reliability has become rather popular and is used extensively by the general public as well the technical community.

When used by the technical community, the context and interpretation of the word becomes rather specific and can deviate substantially from the popular meaning. Reliability is a mathematical concept [10] and there are divergent definitions for reliability used in the context of asset reliability. One of the more appropriate and recently used textbook definitions is "the probability that an item will perform its intended function for a specific interval under stated conditions" [1]. A variation to this definition by

Meeker and Escobar [11] is “the probability that an item will survive until a specific point in time under encountered use conditions”.

At a first glance, both definitions seem to be self-explanatory and misinterpretation appears improbable. However, the definitions contain four distinct aspects, namely probability, function (survive), time interval (point in time) and conditions. Meeker and Escobar [11] highlight the importance of the environment in which the item operates (i.e. the conditions) as a critical factor in evaluating the item’s reliability. This is supported by Puntis [12] who argues that the equipment supplier should define the environment under which the equipment will operate such as the duty cycle, maintenance regime and climatic conditions. However, the user of the item has control over the conditions, which can include the user’s skill, logistic support, maintenance, environment and user demand profile. As such, any numerical measure of reliability is scenario dependent [13].

Besides the importance of the *conditions*, the acceptance standard for the *probability*, *function* and *time interval* must be clear. Without clarity, the definition of reliability will be open for interpretation.

2.1.2 Quality and Reliability

Condra [14] looks at reliability from a different angle when he defines reliability as “product performance over time” and describes it as “another dimension of quality”. Some of the standard definitions for the quality of a product, as summarised by Knezevic and Venkatraman [10], are “it meets or exceeds the customer’s stated or implied expectations“, and/or it “does this consistently, over a long period”. Quality has both subjective and objective dimensions and is normally measured qualitatively depending on individual perceptions [10].

The difference between quality and reliability is that the latter can only be quantified after the item has been in the field for some time [11], and places the emphasis on the constant reliability throughout the lifetime of the item, and the definition of Condra [14] implies that good quality is important and should not be seen in isolation.

2.1.3 The Significance of Reliability

Not all organisations see the value in measuring reliability. As such, Smith and Mobley [15] summarise five reasons why companies do not measure reliability as follows:

1. Not all maintenance work is recorded on work orders and valuable failure information, especially small failures, are not recorded [16].
2. All assets are not loaded on a Computerised Maintenance Management System (CMMS).

3. Other metrics provide an adequate level of information, therefore, it is not important to even measure the most basic Mean Time Between Failures (MTBF).
4. Maintenance is in a fire fighting mode, reacting to crises, with no time to generate metrics.
5. There are too many other problems to worry about.

Although asset intensive organisations should recognise the importance of an effective maintenance function, the tendency in many organisations is to see maintenance as an expense [17] and not a value adding process able to contribute to reliability. The objective of maintenance is to improve reliability and maximise equipment availability [18] through scheduled Preventative Maintenance, Replacements and Inspections (PMRI) [19].

There are many reasons why reliability is important. These include reputation, customer satisfaction, operation and maintenance cost, repeat business and for a competitive advantage [20]. But from a maintenance point of view, reliability will contribute to a higher availability, which is particularly important in the context of RAMS. Reliability of physical assets is an engineering discipline [11] on the one hand. Reliability analysis, on the other hand, is a systematic approach to analyse the reliability of systems, identify and access the frequency and causes of failures in order to control their consequences.[21].

2.2 Maintenance Strategies, Maintenance Techniques and Reliability

According to the standard BS EN 50126 [1], maintenance is “the combination of all technical and administrative actions, intended to retain a product in, or restore it to, a state in which it can perform a required function”. Similarly, maintenance of industrial equipment is defined by Pintelon and Gelders [18] as “all activities necessary to restore equipment to, or keep it in a specified operating condition”. With these definitions and the earlier definitions of reliability, it is clear that maintenance is important in enabling an asset to perform a required function. As such, when maintenance is effectively done, the product can be regarded as “reliable”. Maintenance is, therefore, one of the key drivers to obtain the objectives of reliability. In this regard, as much as 70% of production cost is related to maintenance for some industries, and one third of the total maintenance cost is wasted due to uncertainties and inefficiencies in maintenance planning [22].

Asset maintenance must not be confused with AM. As can be seen in Figure 2.2, the “maintain” function is a single step in the context of AM. AM has more dimensions and is much broader than asset maintenance and focusses on the broader life cycle management dimensions among them economics, physical performance, risk and human dimensions of the asset [4].

Chan and Shaw [23] identify three states of a system illustrated in Figure 2.3 as:

1. Operating State (OS), where the system is *up* and operating, and it can fail.
2. Failure State (FS), where the system is *down* and failed.
3. Maintenance State (MS), where the system is *down* and in Preventative Maintenance (PM), and can either fail and move to the FS state, or be restored to the OS state.

They recognise that a system can either be in an *up* or *down* state, and that during the OS-MS transition cycle, PM transforms the state from *up* to *down*. Similarly, a failure will transform the system from *up* to *down* during the OS-FS cycle, and a renewal or replacement will reverse the state. It is important that the MS and FS be optimised as they both impact on the reliability and availability of the system.

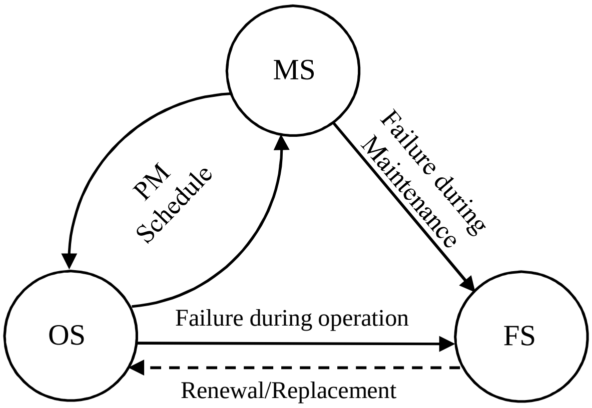


Figure 2.3: State transition of a repairable system with a PM schedule [23]

Pham and Wang [24] found that not all maintenance activities improve the condition of an item. They thus categorise maintenance according to the degree to which the operating conditions of an item is restored. They define the following types of maintenance:

- *perfect maintenance* - which restores the operating condition of the system to as-good-as-new.
- *minimal maintenance* - which leaves the condition as-bad-as-old.
- *imperfect maintenance* - which brings the condition somewhere between the as bad-as-old and the as good-as-new condition.
- *worse maintenance* - which increases the failure rate or actual age of the system, without breakdown.
- *worst maintenance* - which unintentionally causes a failure or breakdown.

Possible causes identified by Pham and Wang [24] for imperfect, worse or worst maintenance include; the repair of the wrong part, partial repair of the fault, replacement with faulty parts and human error.

Maciejewski and Anders [25] proposed an equipment deterioration model based on historical data (refer to Figure 2.4). The purpose of the model is to estimate the remaining life of a piece of equipment under a specific maintenance policy. In their model, the condition of the equipment can either be *D1* (new, or good as new), *D2* (minor deterioration stage), or *D3* (major deterioration stage).

In the event of no operator intervention, the last stage (*D3*) is followed by failure (*F*), which then requires extensive repair or replacement to restore the condition to *D1*. In most cases, however, the operator does intervene according to a maintenance policy, where inspections (*I*) are performed at predetermined intervals followed by either Minor Maintenance (*M* in Figure 2.4), Major Maintenance (*MM* in Figure 2.4) or nothing.

After a minor maintenance is performed, major maintenance may be performed immediately or after a period. The condition of the equipment cannot improve with a minor maintenance as it will either stay the same or deteriorate. After each type of maintenance, the condition of the equipment must be determined, in which case it can improve (perfect maintenance), stay the same or deteriorate (worse or worst maintenance).

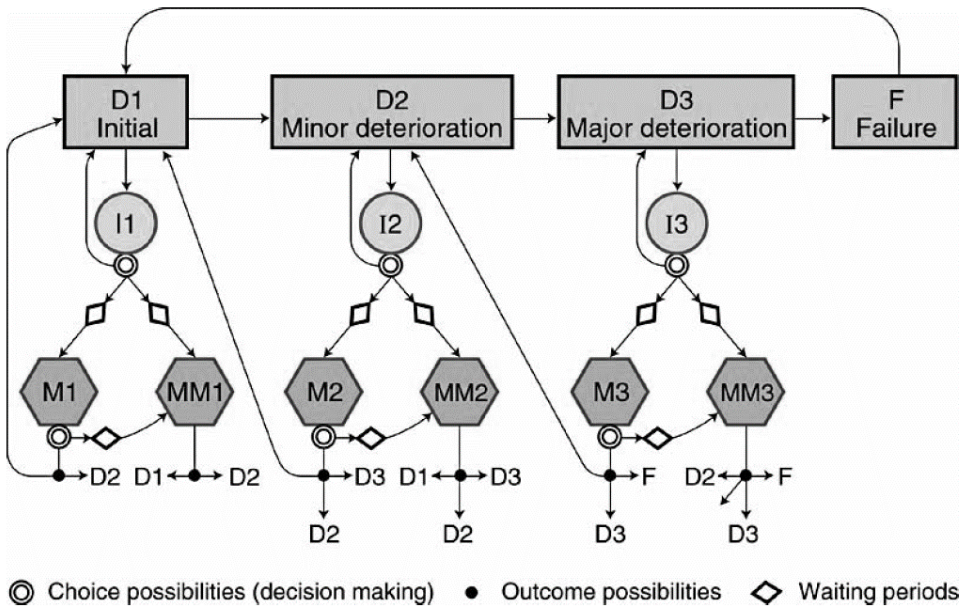


Figure 2.4: Graphical representation of the model of equipment deterioration [25]

2.2.1 Failures and Failure Modes

Before continuing with the discussion on reliability, a common frame of reference with regard to the principles of failures and reliability needs to be defined. A failure occurs whenever a system or component no longer operates within the expected or designed specification. This includes both breakdowns and out-of-specification performance. The definition of a failure is summarised by Coetzee [26] as “an unsatisfactory condition” broadly divided into a potential failure (*P* in Figure 2.5) and a functional failure (*F* in Figure 2.5). Coetzee [26] further refers to potential failures as a specific type of failures, which is one of the greatest contributions by Reliability Centered Maintenance (RCM) to the theory of maintenance. A functional failure occurs when the equipment is not performing its intended function.

A potential failure is a leading indicator which shows that a functional failure is imminent. The severity of the defect and criticality of the asset determines how quick the maintenance response should be. If the defect severity is low and asset criticality is low, then there is no panic. A *PF* interval can be defined as the amount of time that elapses between the detection of a potential failure and its deterioration to a functional failure [15] (refer to Figure 2.5). It is, therefore, essential that maintenance organisations know the PF curve and PF interval on critical equipment to optimally manage the reliability of the plant. It is shown, later in this study, how different maintenance techniques can be used to determine potential failures before they deteriorates to functional failures.

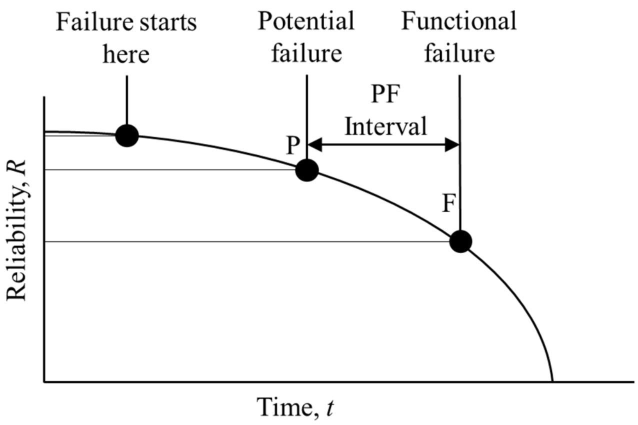


Figure 2.5: Typical failure curve indicating the PF interval [15]

Traditional maintenance practitioners believed that most failures of equipment are age related and a common mistake was to use a single maintenance technique for all equipment. Failure patterns are often used to select the most appropriate maintenance technique where the failure of aging equipment is classified into six traditional failure patterns [27][26], namely:

1. Bathtub pattern, with infant mortality (wear in zone, or running in zone) followed by a period of random failure, then by a wear out zone.
2. Traditional pattern, with an initial random failure rate, with a distinct wear out zone.
3. Slow aging, where the failure rate is gradually increasing throughout the life.
4. Best new, with a steep increase of the failure rate, then settling into a random failure rate.
5. Constant random failure, where the failure rate is constant (random) and not age related.
6. Worst new, with initial wear in followed by a constant (random) failure rate.

It was also believed that most equipment follow the bathtub pattern, but in reality, it is only true for 4% of equipment with the majority following the *worst* new failure pattern [27]. Also, most of the six traditional failure patterns can be managed by periodic Time Based Maintenance activities [28].

Ascher and Feingold [29] define a “happy” and a “sad” system. On the one hand, the inter-arrival times of failures of an improving (“happy” or ☺) system tend to become larger, and the plot of cumulative number of failures will tend to concave down. The inter-arrival times of a deteriorating (“sad” or ☹) system, on the other hand, tend to become smaller, and the plot of cumulative number of failures will tend to concave up. This is illustrated in Figure 2.6 with a small sample of failures.

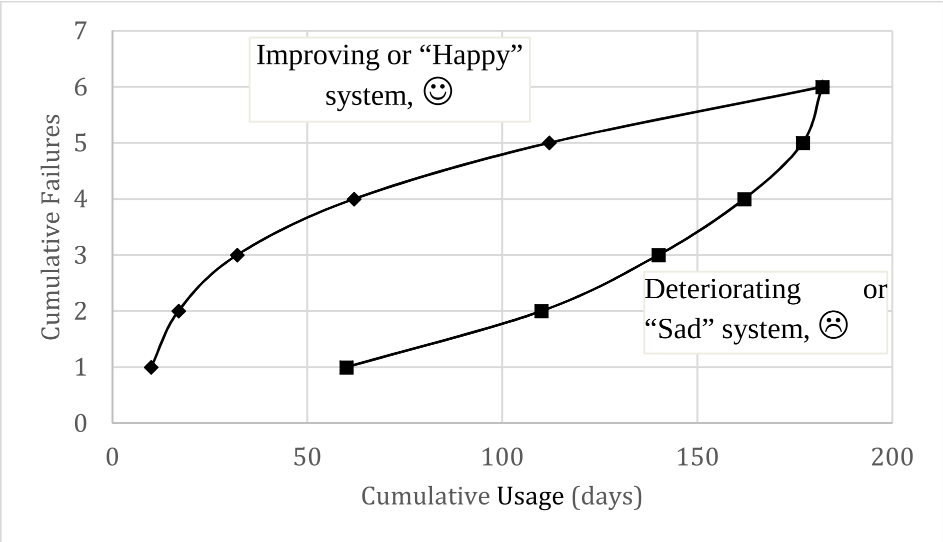


Figure 2.6: Cumulative number of failures vs cumulative usage for “happy” and “sad” systems

For the purpose of this study, it may be convenient to visualise a system as a large number of sockets, each containing a component which may or may not be alike [29][30][31]. Ascher and Feingold [29] define a socket as a “circuit or equipment position, which at any given time, holds a part of a given type”. These parts are subject to failure according to a probability distribution, although a component failure does not necessarily constitute a system failure. Furthermore, not all failures can be prevented by even applying the best maintenance strategy. Thus, such failures need to be predicted using statistical methods. This approach forms the focus of this study.

2.2.2 Maintenance Management Overview

Garg [32] conducted a literature survey on maintenance management and analysed 142 academic papers from which he classified maintenance management into six areas, summarised below and detailed in Table 2.1:

1. Maintenance optimisation models

During the past few decades, mechanisation and automation has reduced the number of production personnel while there was a significant increase in production equipment. As a result, maintenance gained importance as a critical value adding activity. As such, research into optimisation of maintenance is done continuously. Because of the advances in information technology, maintenance optimisation models are used more frequently lately. This quanlitative approach in maintenance optimisation is well covered in literature. Maintenance optimisation covers four aspects [32]:

- An analysis of a technical system, including its function and importance.
- The modelling of the failure trends and deterioration of the system over time with possible consequences.
- A description of the information available and actions open to management.
- An objective function and optimisation technique to suggest the best option.

The models can be classified as deterministic or stochastic, based on the modelling of the deterioration [32].

2. Maintenance techniques and maintenance strategies

A maintenance strategy is made up of one or more maintenance techniques (also called maintenance types). A typical maintenance strategy tree is shown in Figure 2.7. RCM and Total Productive Maintenance (TPM) are the two typical types of maintenance strategies, which will be explained in detail in the sections that follow. Maintenance is also viewed as a multi-disciplinary activity involving integration of different strategies. Other maintenance strategies, which will not be discussed in detail, owing to the scope of this study, are:

- Risk Based Maintenance - optimising cost effectiveness and minimising the hazards caused by unexpected failure.
- Effectiveness Centered Maintenance - where the focus is on “doing the right things”, instead of the traditional “doing things right” [32].

3. Maintenance scheduling

The purpose of maintenance scheduling is to bring together the different elements, which can include manpower, machines, methods, materials and metrics, in order to complete a maintenance activity on time. There are fundamental differences between maintenance scheduling and production scheduling. For example, maintenance scheduling is more stochastic in nature and the scheduling of maintenance personnel makes it a challenging problem.

4. Maintenance performance measurement

The measurement of maintenance performance is difficult. Although in the past it was limited to financial reporting [32], maintenance performance measurement is based on what the user perceives to be important. Whereas the management is interested in budgets, engineers will focus on techniques, equipment availability, support responsiveness, etc. Various measurement techniques can be used among them the balanced scorecard, quality function deployment technique, overall equipment effectiveness, performance measurement relationship with the maintenance strategy and the effect of maintenance induced failures on operational effectiveness [32].

5. **Maintenance information systems**

As already mentioned, the advances in information technology have resulted in more areas of application. Computers are able to stream and store more data, be more flexible in manipulating data, create various types of reports from the data and use data to do effective forecasting. Data mining has become a critical skill for maintenance engineers, and equally so, the ability of business architecture to accommodate the streamlining of data capturing and reporting.

Amadi-Echendu et al [4] mention that the issue of data capture and information technology focus on ways to monitor the condition of assets more effectively in order to prevent premature failure of the asset. Madu [33] acknowledges that effective AM systems is facilitated by IT software, and that AM is dependent on an effective Enterprise Resource System (ERS) that collects data.

6. **Maintenance policies.**

A maintenance policy has an important role to play, that of creating a clear vision of the maintenance function. This has also been highlighted by the AM ISO 55000 standard and illustrated in Figure 2.2.

Table 2.1: Maintenance management classification

Maintenance area	**Sub area**
Maintenance optimisation models	Bayesian approach Mixed integer linear programming formulation Multiple criteria decision making approach Fuzzy linguistic approach Gailbraith approach Simulation Markovian probabilistic models Analytic Hierarchy Process Petrinets

	Organisation modelling
Maintenance techniques	Preventive Maintenance (PM) Condition-Based Maintenance. (CBM) Total Productive Maintenance (TPM) Computerised Maintenance Management Systems (CMMS) Reliability Centered Maintenance (RCM) Predictive Maintenance (PdM) Maintenance outsourcing Effectiveness Centered Maintenance Strategic Maintenance Management Risk-Based Maintenance
Maintenance scheduling	Techniques (e.g. CBM, PdM, PM) Wear out component Repair rate modifying activities Combining production and maintenance Maintenance personnel
Maintenance performance measurement	Techniques (e.g. Balanced Scorecard, Quality Function Deployment, Maintenance Information Systems, Total Maintenance Management, system audit approach) Overall Equipment/Craft Effectiveness Relation with maintenance strategy
Maintenance information system	Opportunity created by information technology Computerises data based info system Development of decision support systems
Maintenance policies	Maintenance integration Maintenance concepts New ideas

Whereas Garg [32] focussed on many elements of an AM system (Table 2.1), the focus in this study will be on the maintenance techniques and maintenance strategies used to manage the physical assets.

2.2.3 Maintenance Strategies and Techniques

The terms maintenance strategies and maintenance techniques were found to be used interchangeably, which was also highlighted by Vlok [31]. Therefore, in the context of this research, a maintenance technique is seen as a sub-task of a strategy. Thus, a strategy is seen as the overall direction an organisation wants to follow, consisting of one or more maintenance techniques.

Maintenance strategies consist of one or more maintenance techniques. These techniques, summarised in Figure 2.7, will be briefly discussed in this section. The traditional maintenance techniques, namely reactive, preventative and proactive maintenance, are often not used independent and the strengths of different techniques are often used to achieve reliable plant capacity [34].

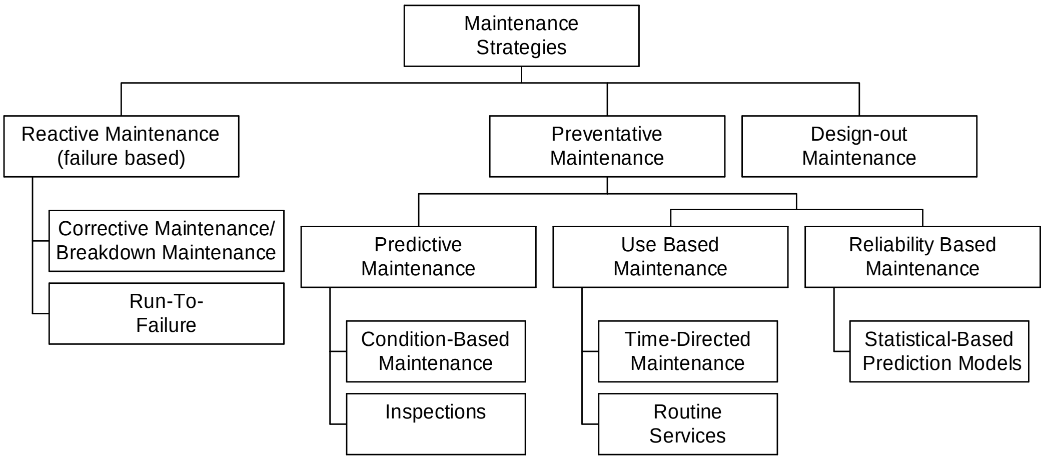


Figure 2.7: Maintenance strategy tree (adapted from [31])

RCM and TPM are typical maintenance strategies used to find the correct maintenance tasks, their frequency and sequence [10]. The failures are identified and the risk/consequence associated with each failure, where after maintenance techniques are then assigned accordingly. For instance,

- when the potential consequences are low and it is difficult to maintain the item, allow the item to run-to-failure (RTF) [10].
- when the potential consequences are not acceptable, minimise them by using CBM, PM [10].

2.2.3.1 Reactive Maintenance

Reactive Maintenance consists of Corrective Maintenance/Breakdown Maintenance and Run-to-Failure. Figure 2.8 shows the process flow of a typical reactive maintenance task, which is triggered by an event. The majority of maintenance activities occur between the triggered event and the completed maintenance. As such, one of the goals of Reactive Maintenance is often, to reduce the response time and equipment downtime to a minimum [15].

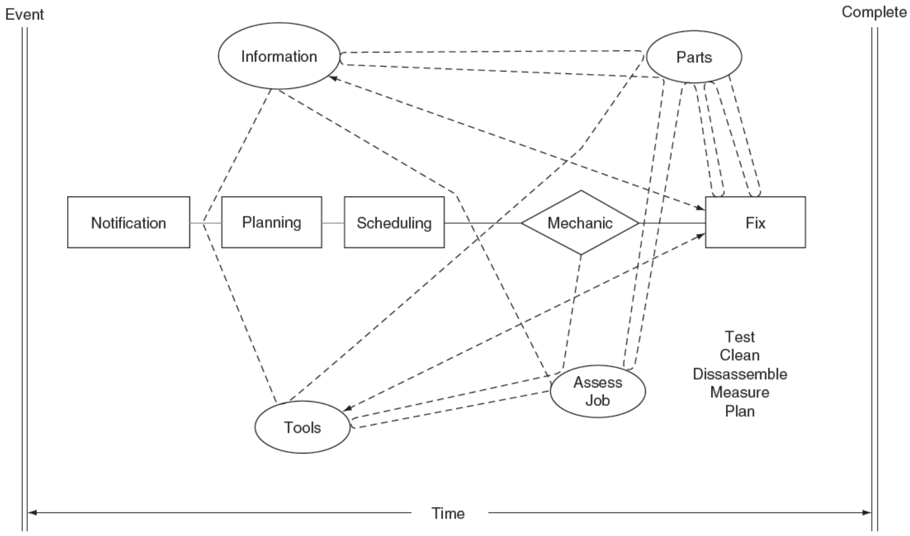


Figure 2.8: Reactive Maintenance model [15]

2.2.3.1.1 Corrective Maintenance/Breakdown Maintenance

Corrective Maintenance/Breakdown Maintenance (CM/BM) refers to all unplanned/unexpected maintenance tasks which are reactive to breakdowns or production interruptions. The main focus of these tasks is to return the equipment back to service as quickly as possible [35] with the perception that the effectiveness of this maintenance is determined by the functionality of the system, as long as the equipment continues to function at an acceptable level [35].

This approach is however, ineffective and results in high maintenance cost with the two contributing factors being:

1. Poor planning resulting from time constraints imposed by production and management while utilisation of manpower and maintenance resources are minimal [35].
2. Incomplete repairs, which only focus on the symptoms of the failure but not the root cause, which can result in a recurring failure.

CM/BM is an unplanned maintenance technique to restore the functionality of the system, thus, it is not formalised and not regarded as good engineering practise.

2.2.3.1.2 Run-To-Failure

With the Run-To-Failure (RTF) technique, the equipment is deliberately allowed to operate until it fails, thus, RTF can be regarded as planned (but unscheduled) maintenance. RTF should only be used under special conditions, when no other maintenance technique is suitable. Although RTF and CM/BM are both Reactive Maintenance techniques, the difference is that there is a clear plan in place for RTF, stipulating the use of spare parts, personnel and methods, therefore, minimising the impact on production. Similar to CM/BM, RTF is unpredictable, costly and requires a large number of spares that may be needed for breakdowns.

2.2.3.2 Preventative Maintenance

Preventative Maintenance (PM) is a series of planned maintenance activities, performed periodically. It aims to manage the *PF* interval (refer to Figure 2.5) by identifying potential failures (*P*) and performing maintenance best suited to the situation. PM is described by Chan and Shaw [23] as repair done on a system while it is in a “not failed” state. The main objectives of PM are to reduce a failure rate that increases because of age [23], prevent Reactive Maintenance, detect critical wear and therefore, extend the life of an asset [36][37]. PM has been used for many years to improve reliability and reduce maintenance costs, and can be seen as the opposite of Reactive Maintenance. Mobley [15] states that PM is limited to lubrication, adjustments and other time-driven maintenance tasks in most organisations, which are not true PM programs.

In contrast to the Reactive Maintenance, PM executes the plan before a failure occurs. Figure 2.9 shows how the planning of schedules and maintenance is done prior to a failure, and how the structured PM approach can achieve the AM objectives.

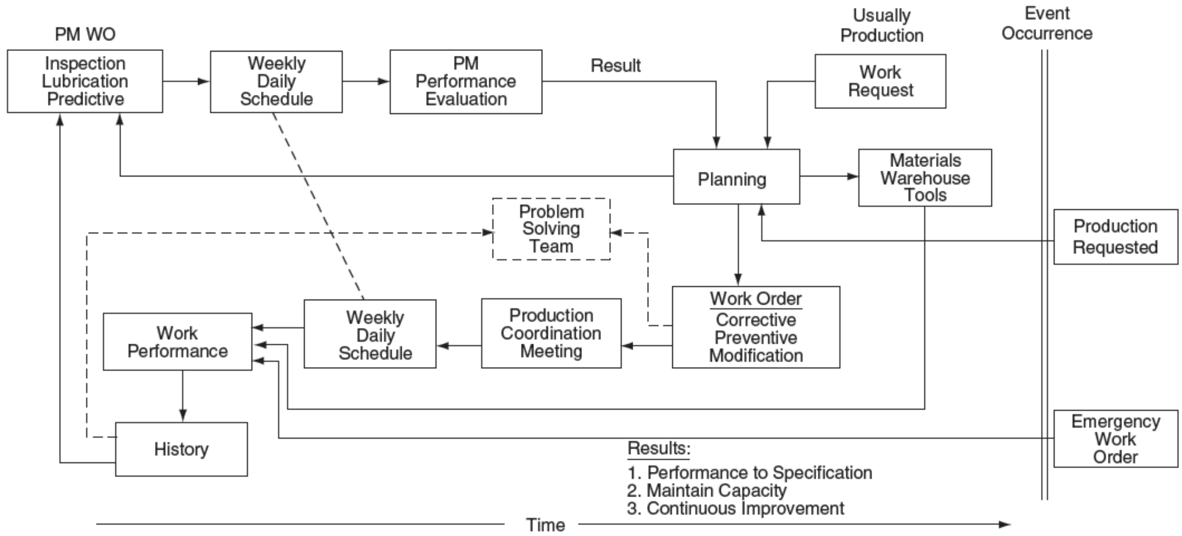


Figure 2.9: Preventative Maintenance model [15]

PM can be regarded as planned scheduled maintenance. The different techniques of PM will now be discussed briefly in the sections that follow.

2.2.3.2.1 Predictive Maintenance

Predictive Maintenance (PdM) consists of any maintenance action whereby the condition of a component is determined and the component replaced before it fails. The condition can be accessed through metrology (diagnostic measures such as temperature, pressure, vibration, speed) used by PdM to optimise total plant operation [38], inspections or statistical methods based on historical data. The latter will be the focus point of this study and will be discussed in detail in later sections of the current chapter.

Metrology is playing a key role in PdM/CBM in various industries and will continue to do so with the advances in the hardware and software of information technology. At the same time, PdM continues to play a critical role with the selection of maintenance strategies and maintenance techniques. But not all components can be monitored with metrology, thus, other methods need to be used to supplement PdM/CBM. Typical examples where metrology cannot be used are the copper wiring of a high voltage DC motor, failure of repairable components due to poor workmanship, etc.

In PM, all inspections are done periodically and are a combination of Time Directed Maintenance (TDM) and PdM [39]. The condition of the item is established, which can then be used to predict a failure making use of PM techniques. Inspections should lead to the detection of failure or the expected onset of failure [39].

2.2.3.2.2 Time Directed Maintenance

Time Directed Maintenance (TDM) is any maintenance activity that takes place based on a measure of time. Appropriate action can be planned such as replacement, overhaul or repair, based on an item's age, which can be measured in time, distance, number of cycles or any other measure.

2.2.3.3 Design Out Maintenance

Design Out Maintenance (DOM) is defined by the Asset Management Council [40] as a maintenance tactic whereby "changes or modifications are done to the equipment to remove a failure cause". When maintenance alone cannot resolve a failure, whether the failure occurred once or more than once, DOM will be used to permanently solve the root cause of the failure.

2.2.3.4 Reliability-Centered Maintenance

Maintenance has evolved since the 1940's from Corrective Maintenance (CM) to a strong focus on PM [32]. Pintelon and Gelders [18] refer to CM as pure "emergency" maintenance where equipment is only maintained when it is inoperable while they refer to PM as "loving care". In the late 1960's, a more integrated maintenance approach between reliability (R) and maintainability (M) was adopted. The term "R & M" also became popular and was followed by the concept of Reliability-Centered Maintenance (RCM) [32].

RCM is a specific implementation strategy of PM [27], defined by four features that characterise and set RCM apart from any other planning process, namely [27]:

1. The most important objective of RCM is to preserve system function in line with the definition of reliability. This ensures that it will not be assumed that every component is equally important, but the context in which the component is related to the function of the system is taken into account. Therefore, in the first step, components which could have a detrimental effect on the functioning of the system must be identified. This can be done using various methods, or by conducting an analysis such as Failure Mode and Effects Analysis (FMEA) or Failure Mode and Effects and Criticality Analysis (FMECA).
2. The second step is to identify the specific failure modes in specific components, which can impair the functions of the system.
3. The third step is to prioritise the importance of the failure modes in order to assign budgets and resources. This is done by interrogating each failure mode by means of a decision tree before categorising the failure modes which will then be used for developing the priority rationale.

4. The last step is to assign PM actions to each failure mode as prioritised in the previous step. Each potential PM action must be applicable and effective in restoring the functionality of the system [27].

Fogul and Petersen [34] define “Reliability Based Maintenance” as a maintenance technique based on the traditional reactive, preventative and proactive maintenance techniques. It is however nothing else than RCM and they list seven breakthrough concepts advocated by RCM as follows:

1. Analysis and prioritisation of system and failure modes of a plant in terms of their impact on capacity and availability.
2. Where to invest maintenance resources, based on maintenance decisions.
3. An optimal combination of preventative, predictive and proactive maintenance technologies.
4. A renewed focus of the maintenance function.
5. Using “breakthrough” practices to redefine the maintenance function, pursue productivity and capacity improvements.
6. Understanding the impact of maintenance decisions throughout the plant.
7. The use of key performance indicators for the maintenance function.

Standards are available to assist with the application of RCM:

- SAE JA1012 - A Guide to the Reliability-Centered Maintenance (RCM) Standard.
- SAE JA1011 - Evaluation Criteria for RCM Processes.

RCM is therefore a powerful strategy which can be used to develop suitable maintenance strategies for assets.

2.2.3.5 Total Productive Maintenance

Total Productive Maintenance (TPM) is a companywide equipment maintenance program involving everyone in the organisation in equipment improvement. Similar to RCM, TPM is an extension of a PM system that was formulated in the 1970’s in the manufacturing industry [32].

Instead of using only maintenance personnel, TPM combines concepts of continual improvement, total quality and employee involvement to achieve the following five goals [15][34]:

1. To improve and optimise overall equipment effectiveness.
2. To improve the efficiency and effectiveness of maintenance.
3. To eliminate equipment breakdowns.
4. To involve the workforce in day-to-day maintenance activities.
5. To continue training of personnel.

With TPM operators take responsibility and ownership of the equipment that they operate, without eliminating the use of maintenance staff.

2.2.3.6 Risk Based Maintenance

Risk Based Maintenance is an alternative maintenance strategy designed to minimise the risk as a result of failures or breakdowns. By using the Risk Based Maintenance strategy, the risk of possible failures are analysed based on the probability and consequence of the failure. The following four steps are followed [41]:

1. Identify the scope.
2. Perform risk assessment.
3. Perform risk evaluation.
4. Perform maintenance planning.

American Petroleum Institute Recommended Practices (API RPs) are available to assist in the application of Risk Based Maintenance, such as API RP 580 and API RP 581. These are not standards and should only be used as guidelines.

2.2.4 Reliability, Availability, Maintainability and Safety

In the first chapter, the contribution of RAMS was discussed. It must be noted that RAMS can be applied to any asset intensive industry but is well documented for the railway industry in BS EN 50126 [1].

As part of RAMS, availability is considered to be one of the most important reliability performance measures of maintained systems [19] and quantifies the "usefulness" of an asset. Availability defines the item "in a state to perform the required function under given conditions…" [1][42]. Reliability and availability are often misinterpreted and in certain cases erroneously used interchangeably. Availability can be defined in terms of Mean Up Time (MUT) and Mean Down Time (MDT) in the following equation:

$$Availability = \frac{Uptime}{Uptime + Downtime} = \frac{MUT}{MUT + MDT} \quad [42]$$

The importance of reliability and availability in the rail industry is best described by Milutinovic [42] who quantifies the influence of reliability on availability as:

$$A = 1 - \frac{S * R * MDT}{MDT + MUT}, \text{ where}$$

S=distance covered in time period MUT

R=number of failures in time period MUT

Reliability can be grouped into the reliability of equipment and the reliability of people [43]. In BS EN 50126 [1], the contribution of humans to railway RAMS is acknowledged and more rigorous control of the human factors is called for. Many studies have been done on the influence of human reliability on asset reliability (refer to Figure 2.10). Karanikas [43] concludes that human errors contribute to more than three quarters of failures during the life of an asset and states that “expecting to achieve perfection from an imperfect human is unrealistic”. Similarly, Vanderhaegen [44] describes the human behavioural degradation when performing tasks and system degradation due to human actions. Amadi-Echendu et al [4] recognise “human dimensions as a key issue in the management of engineering assets”. They find that human capital falls short in adapting to the sophisticated demands of modern AM and that the human factor might be the weak link in the AM chain.

It is clear that all resources required for an effective AM system must be effectively managed. In section 2.2 the contribution of human error towards imperfect, worse or worst maintenance was discussed, and it is therefore acknowledged that human error and human degradation contribute significantly to asset failure and asset reliability. However, none of the authors [4][24][43][44] could quantify the contribution of human error and therefore, in this study, the focus will be primarily on the reliability of assets, and the contribution of human error towards asset reliability will not be isolated or quantified.

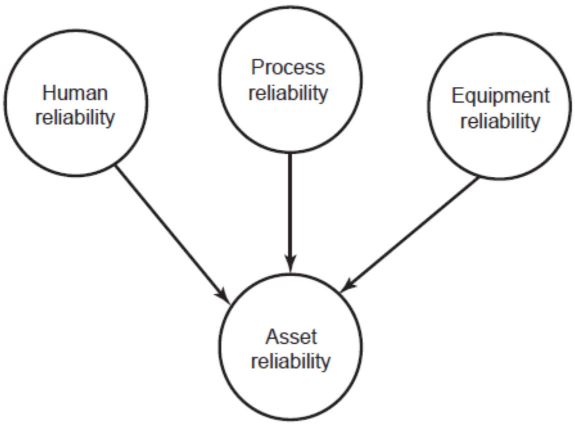


Figure 2.10: Elements of asset reliability [10]

2.2.5 Reliability and Cost

As stated, reliability is important but it should not be pursued at any cost. Ultimately, the cost of maintenance needs to be weighed against the total combined operation and downtime cost. Figure 2.11 is a cash flow diagram where the cost of lost production is shown as a set of peaks and the aggregate impact of lost time can be seen. This aggregate cost proves to be significant if compared to the cost of single breakdowns, and often, this is not considered during the optimising of reliability.

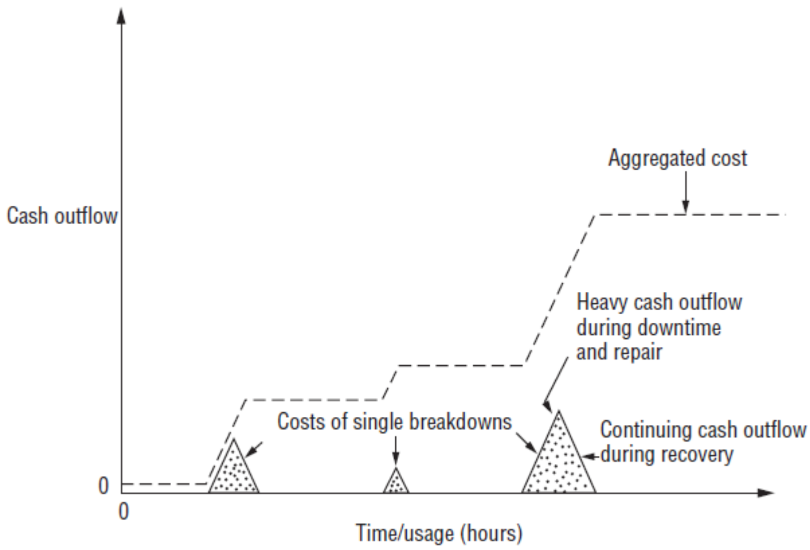


Figure 2.11: Typical cash flow diagram illustrating the cost of lost production [38]

The cost of maintenance must be carefully planned over the complete asset life cycle. Even when the plant is "as new", there will be maintenance cost associated with it when a PM strategy is properly executed. The cost of the PM strategy will rise steadily as the plant deteriorates with age, when the plant will start to require more attention to keep it running smoothly (Figure 2.12).

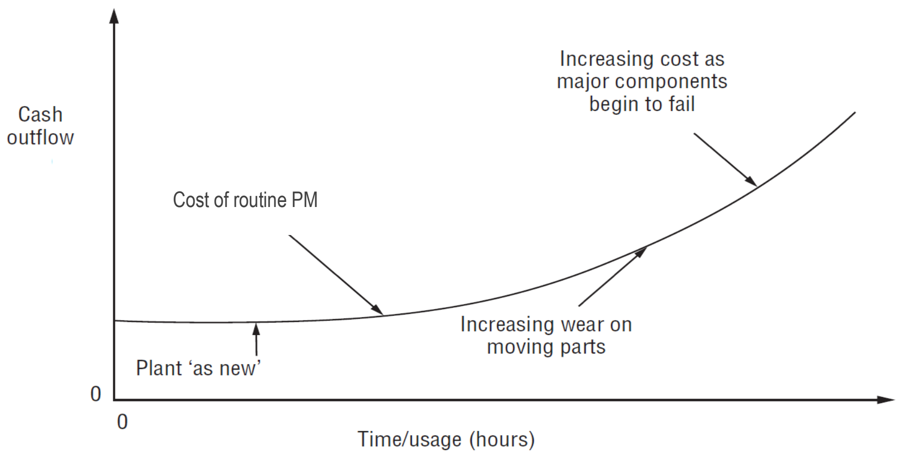


Figure 2.12: Typical cost of a Preventative Maintenance strategy [38]

2.3 Modelling Reliability

In the previous sections, the importance of reliability was shown and different maintenance techniques and strategies were discussed. PM was shown to be advantageous for many reasons, and that PdM is required in addition to PM to optimise cost and to ensure that assets are not "over-maintained". CBM is an effective PdM technique in which metrology may play a critical role in view of future advances in information technology. It was also highlighted that not all components can be measured with metrology and that the use of statistical models based on historical data, will become important in future to supplement the metrology based PdM. This section will describe Reliability Based Maintenance (RBM) and statistical based prediction models, which are shown in Figure 2.7 but were not discussed in the previous section.

The use of statistical models based on historical data will become important in future to supplement the traditional maintenance techniques. By using a CMMS on a well-established and effective ERS, an effective maintenance system can be achieved. With statistical models, failures can be predicted and although not nearly as accurate as predictions from metrology, the statistical models can be used to fill the gaps in CBM.

The rest of this chapter will focus on modelling and quantifying the reliability of physical assets based on historical data, and will discuss statistical techniques used for reliability.

2.3.1 Reliability Systems, Theories and Definitions

During the 1980s, there was a need for the standardisation of reliability terms and definitions, thus, the U.S. Department of Defence published a Military Standard (MIL-STD-721C [45]). This standard became a popular reference by authors, but Ascher and Feingold [29] do not agree with some of the definitions such as the definition for burn-in:

- MIL-STD-721C [45]: "pre-conditioning, defined as the operation of an item under stress to stabilise its characteristics".
- Ascher and Feingold [29] : "the process which results in a decrease of the failure rate or probability of failure, with decreasing number of life units".

This indicates the need to read definitions in the contexts where they are published. For purposes of this study, definitions of reliability of systems will be used from Ascher and Feingold [29], summarised as follows:

- Part: An item which is discarded after the first failure and cannot be disassembled.
- Socket: An equipment position or circuit which, at any given time, holds a specific type of part.

- System: Two or more sockets with their associated parts which are interconnected to perform one or more functions.
- Non repairable system: A system which is discarded after the first time it ceases to perform the function(s) satisfactorily [26][46].
- Repairable system: A system which, after failure to perform at least one of its required functions, can be restored to performing all of its required functions by any method, other than replacement of the entire system.

A non-repairable system is modelled using the renewal theory which is based on the principle that a part is replaced after a failure, the condition restored to the good-as-new condition, and the failures are independent and identically distributed (i.i.d.). The renewal model is regarded as a “poor model” by Ascher and Feingold [29] since most repairs involve the replacement of only a small proportion of the parts after a failure. The renewal theory is not limited only to non-repairable systems because even if a system can physically be repaired (defined as a repairable system), it can still produce failure data that is i.i.d. and can therefore be classified as non-repairable [47].

It might be possible that a repairable system can be restored without having to replace a part and possibly, repair the system by adjustment. Normally, a repairable system is not renewed to the good-as-new condition, but minimally repaired to the bad-as-old condition by the repair or replacement of the failed component(s) [26]. If the failure data has a trend, the condition of the system can deteriorate (or improve) over time and must be modelled using regression techniques [26]. More about trend testing is discussed in later sections of this thesis.

Calculating the reliability of a system requires the mathematical modelling of the system in terms of the interaction of various sub systems. When constant reliability values are used, a snapshot of system reliability is given at a specific time, and when time dependant reliability expressions are used, the system reliability can be observed over a period of time [19].

The uncertainty associated with reliability can be classified as aleatory or epistemic uncertainty. Epistemic uncertainty represents failures caused by a lack of knowledge of the system and can be represented by mathematical structures such as interval analysis, possibility theory, evidence theory and probability theory [48]. Epistemic uncertainty can be reduced by better understanding of the system such as by experimental results or physical models. Aleatory uncertainty is related to randomness and is based on the mathematical structure of probability [48], which is the primary focus of this study.

2.3.2 Overview of System Reliability and RBDs

For more comprehensive insights into the reliability of a system, it is important to be well versed in the configuration of the system. An understanding of the interaction between the system and its larger domain systems as well as its peer systems, sub-systems and components is also important. Bourouni [21] describes a number of reliability assessment techniques and compares the Reliability Block Diagram (RBD) to other reliability assessment techniques (Figure 2.13). He describes the RBD as the most logical and natural representation of a system showing how units (components or sub systems) are logically linked in series, parallel or combinations thereof.

When units are linked in series, the failure of any unit results in system failure, and the reliability of a series system is the product of the individual reliabilities, represented by:

$$R = \prod_{i=1}^{n} R_i \tag{1}$$

where n is the total number of units in the system and R_i the individual reliability units.

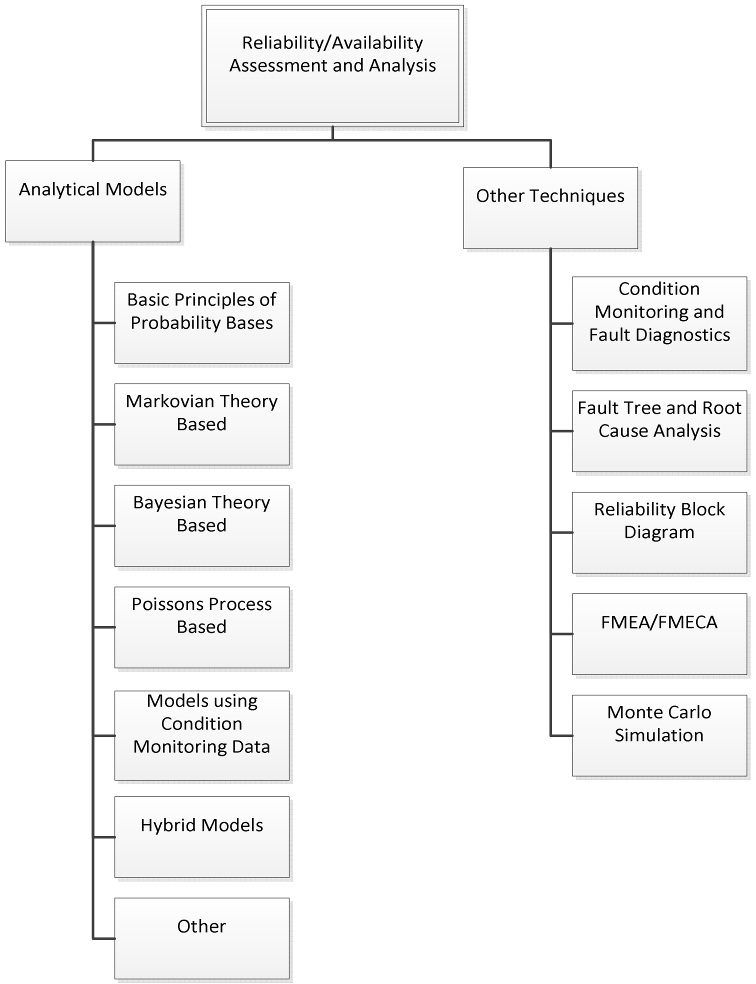


Figure 2.13: Techniques for reliability and availability assessment [21]

Units linked in parallel allow for redundancy and the system remains operational even if only one unit is operational. The reliability of a pure parallel system can be calculated from the individual unreliabilities as shown below.

$$R = 1 - \prod_{i=1}^{n} F_i \tag{2}$$

where n is the total number of units in the system and F_i represents the individual unreliability of each unit defined as $1\text{-}R_i$.

Unlike a pure series system where the failure of a single unit results in system failure, or where a single unit needs to be operative in a parallel system, there are special variations where the system only operates when a certain number of units are operative in a certain sequence (*k*-out-of-*n system)* [20]. There are three variations of the *k-out-of-n system*, listed and described briefly below:

1. In the series configuration, the *consecutive k-out-of-n system* only fails if more than *k* consecutive units have failed [19].
2. In a *balanced k-out-of-n system*, the failure of one unit can force the shutdown of another unit when in a particular arrangement [19].
3. In the *general k-out-of-n system*, redundancy can be built into parallel systems where the system is operational when at least *k* units out of a total *n* units are operational, and the reliability of the system can be calculated as follows:

$$R = [\sum_{l} (\prod_{i} R_i \prod_{j} F_j)] + \prod_{y=1}^{w} R_y \quad [19] \tag{3}$$

where *l* is the total number of possible combinations,
i : items required to survive
j : items allowed to fail
w : total number of units in the system

The *general case of k-out-of-n systems* is often adequate to model a system and the pure series and parallel systems are special cases of the *general k-out-of-n system*. When the system is operational when only one unit is operational, it can be denoted by the *general 1-out-of-n system,* which in turn is a pure parallel system. When the system is only operational when all the units are operational, it is a *general case of n-out-of-n systems* simplified by a series system.

2.3.3 Statistical Analysis of Failure Data for Repairable Systems

Reliability is considered as the science of failures [21] and the purpose of the reliability engineer is to analyse trends in failure data, and determine the Rate of OCcurrence Of Failures (ROCOF) as accurately as possible. The ROCOF represents the number of failures per unit time, and a common erroneous approach used by reliability engineers is to use only the MTBF in calculating the ROCOF, ignoring the chronological order of failure events. The result thereof is that an assumption is indirectly made that failures occur randomly over the given period, and the opportunity to model failure trends is lost. This is illustrated in Figure 2.14, where three scenarios are shown with an equal MTBF, although the opportunity to model a "happy" or "sad" system is lost.

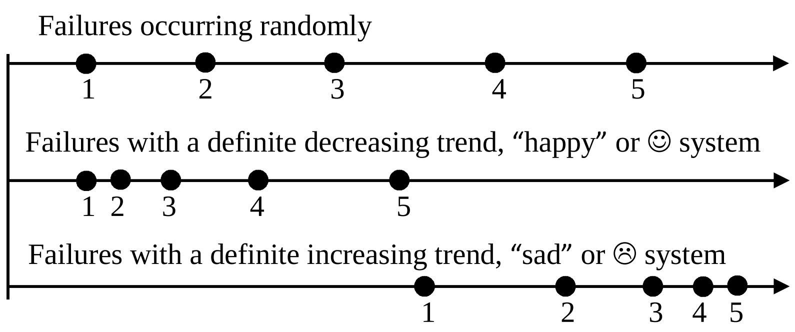


Figure 2.14: Illustrating the risk of using only MTBF

A practical framework for the analysis of failure data [29], modified by Coetzee [49] and Vlok [31], is shown in Figure 2.15. The framework suggests that before a failure distribution can be fitted, failure data should first be tested for a trend (Test 1 in Figure 2.15) and with no trend present, the dependency of failures should be determined (Test 2 in Figure 2.15). A test for dependence is applicable where a primary failure has a positive probability of triggering one or more subsidiary failures. An example is where a primary failure causes a secondary failure which is not detected until the system is put back into operation [29]. With no trend present in the failure data, the failure process can follow a renewal process where repair activities bring the condition of the system back to a "good as new" condition. Ascher and Feingold [29] and Vlok [31] find that the test for dependence (Test 2 in Figure 2.15) is most often omitted because:

- A large number of failure observations are required to perform the test with reasonable confidence.
- There are complexities involved in implementing and interpreting the test, relative to trend testing.
- The lack of understanding of the need to perform this type of test.

Therefore, with the absence of large number of failures and the uncertainty around the purpose of the dependence test, the test for dependence will also be omitted in this study.

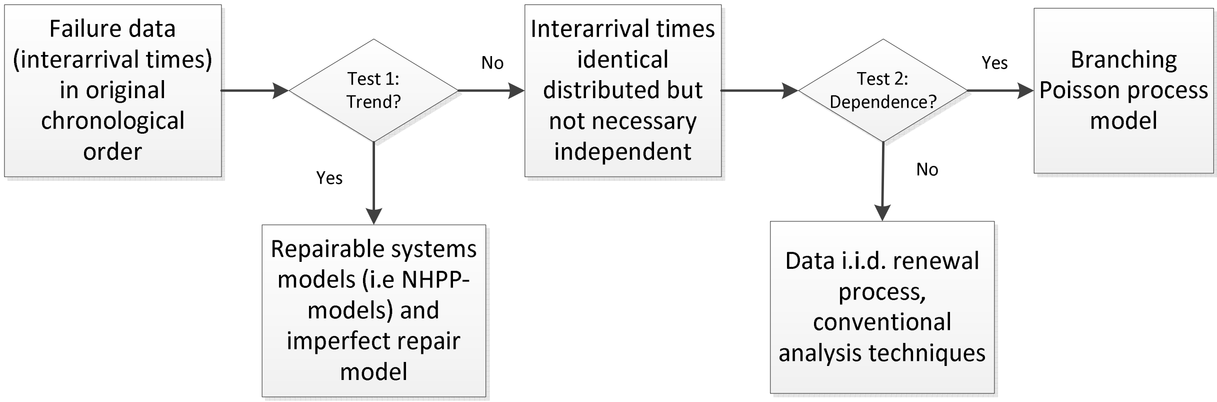


Figure 2.15: Framework for the analysis of failure data, adapted [29,31,49]

A short description will now follow on the methodology employed in the study, based on the framework in Figure 2.15. After a graphical assessment of the failure data is done to observe a failure trend, a numerical validation is done to confirm the result from the graphical assessment. Once a trend or no-trend is confirmed, the most appropriate distribution must be selected, which will best describe the failure behaviour. The parameters for the selected failure distribution are then calculated and the level of confidence calculated to demonstrate how well the parameters fit the selected distribution.

The methods for the above will be discussed in the remainder of this chapter.

2.3.3.1 Graphical Assessment of Failure Behaviour

Ascher and Feingold [29] describe three graphical procedures which can be used to determine whether a system is deteriorating or improving. Not only will procedures be useful to understand the most important features of the failure data, but also helpful to check the initial assumptions after the distributions are fitted to the failure data. The three procedures described by Ascher and Feingold [29] are:

1. Plotting cumulative failures versus cumulative time on linear paper.
   In this plot, the number of cumulative failures are plotted against the cumulative time (or usage). The graph is also known as the ROCOF plot [50]. If the ROCOF is constant, the plotted points will roughly be aligned, hence, the times between successive failures are identically distributed (marked "IID" in Figure 2.16). If the times between successive failures are decreasing, the curve presents a trend with larger increments in the number of failures per unit time. The tail end of this curve tends to concave up indicating reliability deterioration (marked "Deterioration" in Figure 2.16, also a "sad" system or ☹). Reliability growth is the opposite when the times between successive failures are increasing and the graph concaves down with smaller

increments in the number of failures per unit time (marked "Growth" in Figure 2.16, also a "happy" system or ☺).

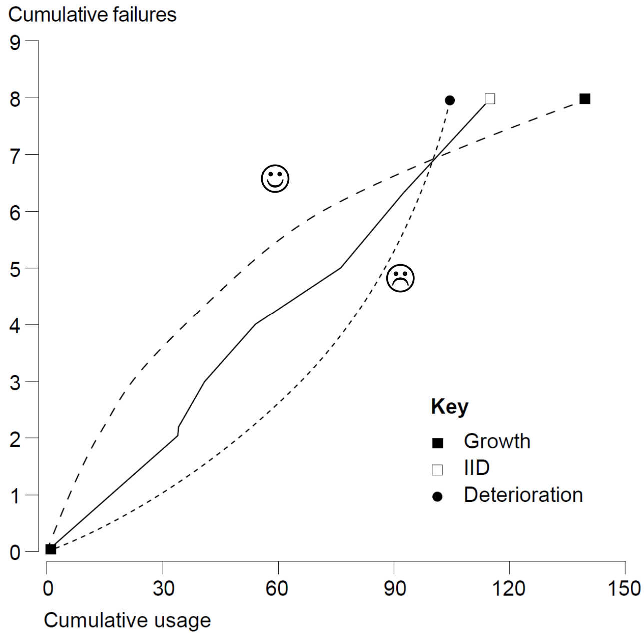


Figure 2.16: Graphical assessment of trends in failure data [50]

2. Estimating average ROCOF in successive time periods.

   Ascher and Feingold [29] observe that local variations in the failure rate will be masked because of the monotonically increasing nature of the cumulative number of failures plot. An alternative is to divide the observation period into a number of equal subintervals and plot the average ROCOF for each subinterval, calculated as:

   $$v_i(t) = \frac{N_i(t) - N_{i-1}(t)}{\Delta t}, (i-1)\Delta t < t < i\Delta t$$

   where $N_j(t)$ is the total number of observed failures from $t=0$ to $t=t_j$.

   When a system is deteriorating, $v_i(t)$ with $i=1,2,\ldots$ will tend to increase because more failures occur within a subinterval. The same applies for a system that is improving, where $v_i(t)$, $i=1,2,\ldots$ will tend to decrease. A disadvantage of this procedure, identified by Ascher and Feingold [29], is that the selection of different subinterval lengths will result in different conclusions. The selection of one subinterval length only will not give the best results necessarily, thus, different selections should be tested and compared.

3. Duane plots.

   In 1964, Duane [51] introduced a learning curve approach to reliability monitoring. The model was developed for the aircraft industry, where he found that electromechanical and mechanical systems follow simple and predictable failure patterns. Duane [51] plotted the cumulative failure rate (which is defined as the total number of failures since the program was first used) divided by the total operating hours since first use, on log-log scales and found consistent straight line plots.

In order to summarise graphical failure trends, typical trends will be discussed. Gilbert [52] identifies eight types of trends applied in environmental pollution, which are applicable to any industry (refer to Figure 2.17 for detail). The trend types are listed as follows:

1. Random trend, which is a sequence of measurements where the fluctuations along the sequence are due to unassigned and random causes.
2. Cycle and random, with no long term trend.
3. Trend and random, which refers to random fluctuations with a growing linear trend.
4. Trend and cycle and random, which consist of random fluctuations within a cycle with a growing linear trend.
5. Trend and non-random, where a growing trend is present with non-random causes.
6. Random with impulse, which refers to a random trend with a short lived impulse.
7. Step change plus random, which is similar to the “random with impulse”, but with a more permanent step change.
8. Random followed by trend, which is a sequence of random measurements fluctuating about a constant level with a growing trend.

Although it is suggested by Gilbert [52] that the eight trend types are applicable to any industry, which can be used to categorise the performance of an asset, it does not add value to the understanding of reliability growth or reliability deterioration. These trends can be identified in failure data, although it will not add value to the interpretation of how the system performed.

Therefore, this study will be limited to the three graphical techniques suggested by Ascher and Feingold [29] to determine whether a system is deteriorating or improving.

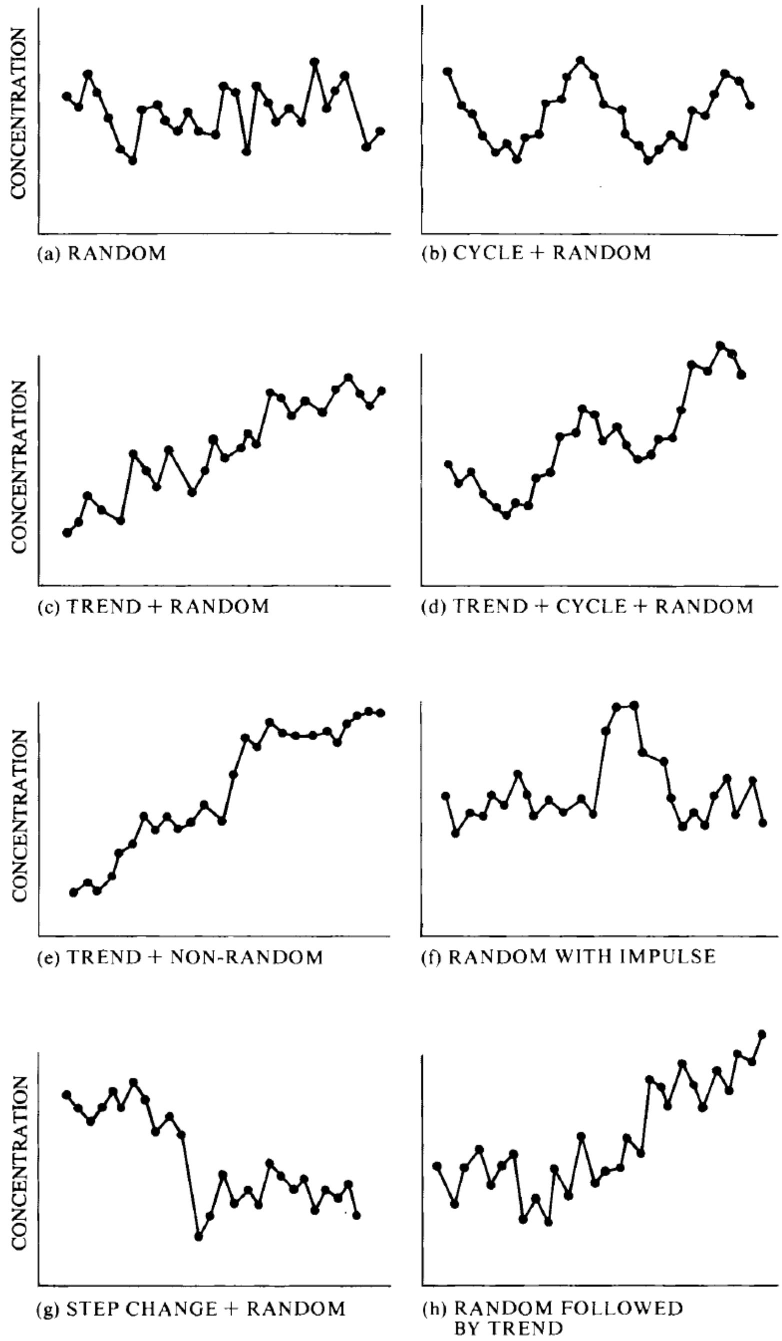


Figure 2.17: Eight types of failure trends [52]

2.3.3.2 Numerical Trend Tests

In the previous section, the graphical assessment of the trend in failure data was discussed. As discussed earlier, the purpose of the graphical assessment of the failure data is to observe a failure trend, but a numerical validation is still required to confirm whether the results from the graphical assessment are correct. Although there are many techniques for calculating trends, the focus in this study will only be on three trend tests, which are discussed below.

2.3.3.2.1 Basic Notations

Before discussing the detail of trend testing, there are some important notations and definitions that need to be clarified. Firstly, in a system, events are recorded on a continuous global time *t*, and numbered from event 1 up to *r*, where *r* is the total number of events. The arrival times (also called *times to events)* $T_1, T_2, \ldots T_r$ is defined as the times when the events occur, measured in global time, where T_1 denotes the first event, T_2 the second event, and so on. Similarly $X_1, X_2, \ldots X_r$ is the inter-arrival times (also called *times between events)*, measured in local time, where $T_n = X_1 + X_2 + \ldots + X_n$ and $X_n = T_n - T_{n-1}$. These concepts are illustrated in Figure 2.18.

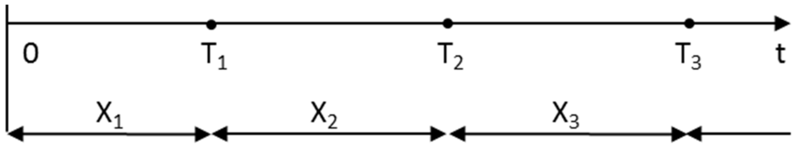


Figure 2.18: Arrival times T_n and inter-arrival times X_n

Secondly, an integer counting process *N(t)* is defined as the number of events which occurred in (0,t], which will include both the number of failures, *N(t)*, and the instances of occurrence, $T_1, T_2, \ldots$[31].

Lastly, during PM, components are repaired or replaced even when not all these components have failed. For failure analysis, this is regarded as truncated failure time observations (also called suspensions) because the component survived up to the age of PM but it is not known when the component would have failed if left undisturbed [31]. A variable C_i is recorded with each X_i indicating whether X_i was a truncated failure observation (C_i=0) or a “real” failure (C_i=1) and this will influence the approach when manipulating the data.

2.3.3.2.2 Laplace Trend Test

The Laplace Trend Test (LTT) [26] [29] is the most extensively used trend test for data sets [31], and was therefore chosen for this purpose in this study. The test is effective for calculating a trend where all the events are real failures. The trend parameter U_L can be calculated by:

$$U_L = \frac{\frac{1}{r-1}\sum_{i=1}^{r-1} T_i - \frac{T_r}{2}}{T_r\left[\frac{1}{12(r-1)}\right]^{\frac{1}{2}}} \qquad (4)$$

where $T_1, T_2, \ldots, T_r$ = arrival times of failures,

r = total number of observations [26][31]

The null hypothesis (H_0) for the LTT is that the distribution of the arrival times corresponds to a Homogeneous Poisson Process (HPP) if the rejection criteria is met [53], otherwise the Non Homogeneous Poisson Process (NHPP) is followed. A HPP is a stochastic time based process, where the inter-arrival times are i.i.d. The rejection criteria is based on a standard normal distribution assumption, and it will reject H_0 if $U_L > z_{\alpha/2}$ or $U_L < -z_{\alpha/2}$ [53]. Based on a typical 95% confidence level (α=5%), H_0 will be rejected if $U_L>1.96$ or $U_L<-1.96$, and if $U_L=0$ it means that the trend is a horizontal line. For simplicity, the rejection criteria is approximated as $U_L>2$ or $U_L<-2$. Ascher and Feingold [29] find that the test is effective for $r\geq 4$.

Coetzee [26] interprets the value of the LTT value U_L in Table 2.2, and from the results the type of theory can be selected. Once the renewable theory or repairable system theory is selected, a family of distributions can be selected and the parameters determined with the most appropriate method.

Table 2.2: Interpretation of the LTT value U_L [26]

Value of *u*	**Description**	**Type of theory**
$-2< U_L<-1$, $1< U_L <2$	Grey area, more tests required	Either renewal theory or repairable systems theory
$U_L <-2$	Reliability improvement, data non-homogeneous	Repairable system theory, use NHPP
$U_L >2$	Reliability degradation, data non-homogeneous	Repairable system theory, use NHPP
$-1< U_L <1$	Non-committal, data homogeneous	Renewable theory, use HPP

A shortcoming identified by the author in the LTT is that the test does not account for the discrepancy when the last failure is not near the end of the observation period. Consider the hypothetical case in Figure 2.19 where $X_1=X_2=X_3=X_4=100$ days, and $X_5=1000$ days. The following LTT values for U_L can be calculated:

- $U_L(T_1 \to T_4) = 0.866$, which indicates the data is non-committal and homogeneous.
- $U_L(T_1 \to T_5) = -1.217$, which is in a grey area and indicates that the data follows either the renewal theory or repairable systems theory.

It is therefore important that the LTT calculation should not be done blindly, without questioning the data and the results. The author compensated for this by selectively adding a failure point at the end and/or at the beginning of the observation period. Therefore, some components can have one or more truncated failure observations (also called suspensions), where the last failure data points of the data set are not failures, but merely the beginning or end of the observation period.

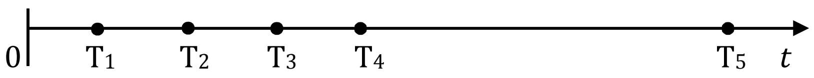


Figure 2.19: Illustrating the shortcoming in the LTT

When the LTT U_L value is within the grey area (-2< U_L <-1, 1< U_L <2), further tests can be performed such as the Lewis-Robinson test [53], Mann-Kendall test [54], Weibull test, Carroll-Hung method [55] to determine whether the data has a trend. The Lewis-Robinson test and Mann-Kendall test will be discussed further.

2.3.3.2.3 Lewis-Robinson Trend Test

According to Coit [53], there is a danger of drawing the wrong conclusions when the H_0 of the LTT is rejected. The Lewis-Robinson (L-R) test is a modification of the LTT where the H_0 is the distribution of the arrival times corresponds to a Renewal Process (RP). The *L-R* statistics (U_{LR}) can be defined in terms of the LTT value U_L and the coefficient of variation *(CV)* of the inter-arrival times as:

$$U_{LR} = \frac{U_L}{CV} \tag{5}$$

CV can be calculated as

$$CV[X] = \frac{\sqrt{Var[X]}}{\overline{X}}$$

Where $\sqrt{Var[X]}$ is the standard deviation of the inter-arrival times, and $\overline{X}$ the mean of the inter-arrival times.

Like in the case of the LTT, H_0 will be rejected if $U_{LR} > z_{\alpha/2}$ or $U_{LR} < -z_{\alpha/2}$ [53]

2.3.3.2.4 Mann-Kendall Trend Test

The last trend test that will be discussed is the Mann-Kendall (MK) test. The MK test statistic is defined in terms of the consecutive inter-arrival times. It is based on a test statistic *S*, calculated as follows [56]:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \operatorname{sgn}(x_j - x_i) \tag{6}$$

where

$$\operatorname{sgn}(\theta) = \begin{Bmatrix} 1, if \theta > 0 \\ 0, if \theta = 0 \\ -1, if \theta < 0 \end{Bmatrix}$$

The test is based on a *S* statistic and a MK probability value. As indicated, the *S* statistic is the sum of the differences between sequential inter-arrival events calculated for the full population of events. The

MK value is obtained from the MK probabilities (Table 6.2 in Appendix B), where the sign of the *S* value is ignored when used in the table.

The MK H_0 assumes that the data set is independently distributed with no trend against the alternative hypothesis H_A of an upward trend. H_0 will be rejected in favour of H_A if the *MK* value is less than a significance level α. To test H_0 against H_A of a downward trend, accept H_A and reject H_0 if *S* is negative and if *MK* is less than α.

2.3.3.3 Parameter Estimation

The estimation of the parameters from failure data can be done using techniques such as the Least Squares Estimation (LSE), Maximum Likelihood Estimation (MLE) and Newton-Rapson algorithm. Only the LSE technique will be discussed further.

2.3.3.3.1 Least Squares Estimation Method

The LSE is a method where the sum of the squared errors is minimised. Consider the errors in Figure 2.20, where the parameters of a line (for example, the parameters *m* and c in the equation $y=mx+c$) need to be determined so that the sum of the squared errors ($e_1^2+ e_2^2+e_3^2+e_4^2$) is as small as possible. For the NHPP, the LSE value was calculated from the observed number of failures and the calculated number of failures ($N(t)$).

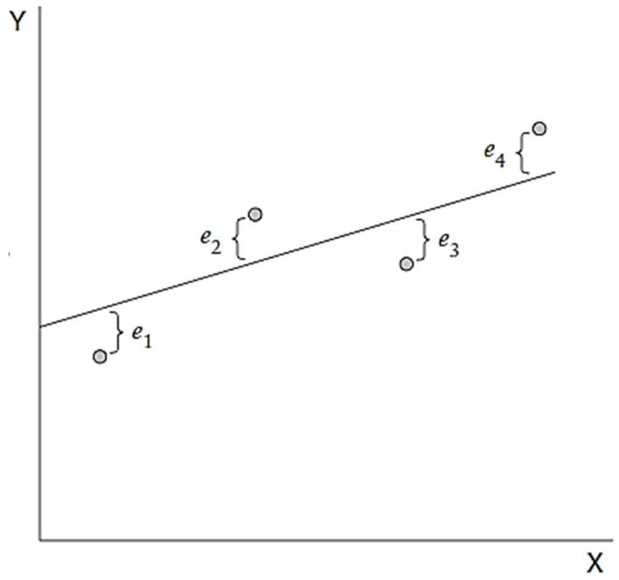


Figure 2.20: Illustrating the errors for LSE

2.3.3.3.2 Linear Regression Method

For the estimation of the two parameter Weibull distribution, linear regression can be done. In order to perform linear regression, the Weibull cumulative distribution (*F(x)*) must be rewritten into a linear format, i.e. $y=mx+c$ as follows:

$$F(x) = 1 - e^{-(\frac{x}{\eta})^{\beta}}$$

$$1 - F(x) = e^{-(\frac{x}{\eta})^{\beta}}$$

$$\ln(1 - F(x)) = -(\frac{x}{\eta})^{\beta}$$

$$\ln(\frac{1}{1 - F(x)}) = (\frac{x}{\eta})^{\beta}$$

$$\ln(\ln(\frac{1}{1 - F(x)})) = \beta \ln(\frac{x}{\eta})$$

$$\ln(\ln(\frac{1}{1 - F(x)})) = \beta \ln x - \beta \ln \eta$$

Where $\ln(\ln(\frac{1}{1 - F(x)}))$ corresponds to *Y*, $\ln x$ corresponds to *X*, β corresponds to *m*, and $\beta \ln \eta$ corresponds to *c*.

Also, in preparation for linear regression, the plotting position of the *F(x)* value must be calculated. There are many plotting position formulas such as Gringorten, Cunnane, Kimball and Blom, as summarised by Kim [57]. The median rank plotting position method, similar to that of Cunnane is used for the Weibull linear regression, where:

$$F_0(x) = \frac{O_i - 0.3}{n + 0.4}$$

Finally, a linear regression calculation can then be used to determine the parameters where η can be obtained from the regression results, which is the slope of the line, and $\eta = e^{-(\frac{c}{\beta})}$.

2.3.3.4 Kolmogorov-Smirnov Goodness-of-Fit Test

The purpose of a goodness-of-fit test is to determine the confidence bands of a distribution function. Although there are many goodness-of-fit techniques, Gilbert [52] observes that the non-parametric Kolmogorov-Smirnov (KS) test is more powerful than other tests. This KS test will be the focus of this section. Many other tests are modifications of the KS test such as the Anderson-Darling test, Cramér-von-Mises test and the Lilliefors test [58].

The purpose of the test is to check whether an observed cumulative step-function of a population $S_n(x)$ fits a hypothetical cumulative distribution function $F_0(x)$. Massey [59] explains the test procedure by drawing the $F_0(x)$ on a graph, and then draws a confidence curve above and below the $F_0(x)$ (see Figure 2.21). The confidence curves are calculated as follows:

- The curve above = $F_0(x)+d$
- The curve below = $F_0(x)-d$

where d is obtained from the KS-table (Table 6.3 in Appendix B), based on the confidence level α. It is shown as:

$$F_0(x) - d_\alpha(N) < S_n(x) < F_0(x) + d_\alpha(N) \tag{7}$$

The observed cumulative step function $S_n(x)$ is then plotted and when $S_n(x)$ passes outside any confidence band, the hypothesis (that of $F_0(x)$ taken to be the true distribution at the α level of significance) will be rejected.

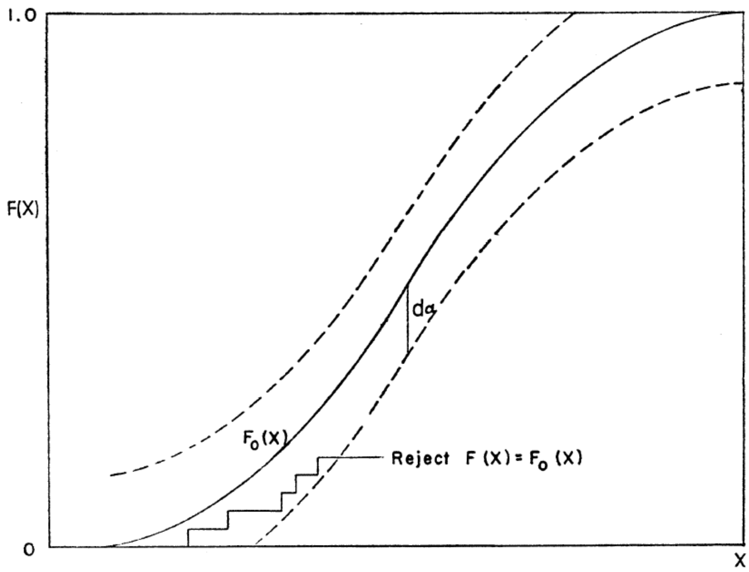


Figure 2.21: Graphical method of applying the KS test [59]

Alternatively, the *KS* test statistic can be used, defined as:

$$D_n = \sup_{x \in R} \left| S_n(x) - F_0(x) \right| \text{ [58].}$$

The D_n value is then used in the KS-table (Table 6.3 in Appendix B) to obtain a d value.

2.3.4 Non-Repairable Systems

The definition of a non-repairable system is given previously as "a system which is discarded after the first time it ceases to perform the function(s) satisfactorily [26][46]". The failure data for a non-repairable system is i.i.d. based on the trend tests, and failures in the data set can be assumed to come from the same statistical distribution, independent from one another. The data is homogeneous, which means that the order in which the events occurred is not important and the failure data can be represented by various standard distributions [29].

There are a number of distributions which can be used to model homogenous failure data and the Weibull distribution (refer to Table 2.3) is one of the most commonly used and flexible lifetime distributions [60]. Substantial research has been done on more applications of the Weibull distribution such as by Unkle and Venkataraman [61] who found synergy between the Weibull and the Army Material Systems Analysis Activity (AMSAA) models. Xie and Lie [62] developed an additive Weibull distribution to represent the bathtub-shaped failure rate data with a single distribution, that is related to the exponential and Weibull distributions. For the same purpose they developed the new Weibull distribution, and when the shape parameter (β) <1, the lifetime data has a bathtub shaped hazard rate function.

There are four functions associated with the failure analysis of non-repairable systems ($f(x)$, $F(x)$, $R(x)$ and $z(x)$), which are:

Failure density ($f(x)$): Also called the probability density function, which provides the probability of failure at instant x [26].

Cumulative Failure Distribution $F(x)$: The probability of failure before or at a certain age. When $f(x)$ is integrated with respect to x, the probability of system failure before a certain instant is obtained [31], with $0 \leq F(x) \leq 1$.

Survival Function $R(x)$: The probability that a component will survive up to a point in time where $R(x) = 1 - F(x)$, $0 \leq R(x) \leq 1$.

Hazard Function $z(x)$: Also called the conditional intensity/failure intensity/Force of Mortality (FOM). It gives the probability that a component will fail at a certain life, where $z(x) = f(x)/R(x)$.

The mathematical connection between these functions are shown in Table 2.3 and they can all be used in the modelling of failures of non-repairable systems. The functions are shown in Table 2.3, applied for the exponential distribution and two parameter Weibull distribution.

The exponential distribution, that assumes a constant failure rate, is a special case of the Weibull distribution with $\beta=1$ and $\lambda=1/\eta$. In the two parameter Weibull distribution, the shape parameter β and characteristic life η parameters can provide valuable information regarding the component in question. As already discussed in a previous section, the parameters can be determined using various techniques.

Table 2.3: The relation of *f(x), F(x), R(x), z(x)* [26], exponential and Weibull distributions [19][26]

Expressed by	*F(t)*	*f(t)*	*R(t)*	*z(t)*
F(t)=	-	$\int_0^t f(u)du$	$1-R(t)$	$1-e^{(-\int_0^t z(u)du)}$
f(t)=	$\frac{d}{dt}F(t)$	-	$-\frac{d}{dt}R(t)$	$z(t).e^{(-\int_0^t z(u)du)}$
R(t)=	$1-F(t)$	$\int_t^\omega f(u)du$	-	$e^{(-\int_0^t z(u)du)}$
z(t)=	$\frac{\frac{dF(t)}{dt}}{1-F(t)}$	$\frac{f(t)}{\int_t^\omega f(u)du}$	$-\frac{d}{dt}\ln R(t)$	-
Exponential distribution	$1-e^{-\lambda x}$	$\lambda e^{-\lambda x}$	$e^{-\lambda x}$	λ
Weibull distribution	$1-e^{-(\frac{x}{\eta})^\beta}$	$\frac{\beta}{\eta}(\frac{x}{\eta})^{\beta-1}e^{-(\frac{x}{\eta})^\beta}$	$e^{-(\frac{x}{\eta})^\beta}$	$\frac{\beta}{\eta}(\frac{x}{\eta})^{\beta-1}$

The mean life of the Weibull distribution is [19]:

$$E[T(time-to-failure)]=\eta.\Gamma\left(1+\frac{1}{\beta}\right) \quad (8)$$

where $\Gamma(n)$ is the gamma function and the values for n are obtained from the Gamma Table 6.4 in Appendix B.

For a non-repairable system, the trend tests already confirmed that the life data is independent and identically distributed (i.i.d.). For the Weibull distribution, the shape parameter (β) can provide an indication whether the hazard rate is increasing ($\beta>1$) or decreasing ($\beta<1$). If the shape parameter equals unity ($\beta=1$), the intensity function ($z(x)$) remains constant, the system has a constant FOM therefore the instantaneous risk of failure remains constant throughout the life of the system (as the case of the exponential distribution). The η is the characteristic life, which is an indication of the expected life and also an indication of the age at which 63.2% of the components will fail [26].

In the case of *perfect maintenance* which restores the condition of the system to the "good as new" condition, the failure process is called a renewal process. Times between failures are i.i.d. and a special case is the HPP Repairable systems. A repairable system can be restored to perform the intended function without the complete replacement of the system. It is often modelled as a counting failure process and the analysis of repairable systems must consider the effects of successive repair actions [53].

2.3.5 Repairable Systems

The definition of a repairable system was discussed earlier as "a system which, after failure to perform at least one of its required functions, can be restored to performing all of its required functions by any method, other than replacement of the entire system."

Repairable systems are represented by non-homogenous data and can best be modelled by the NHPP [26][31][49]. The NHPP is generally suitable for the purpose of modelling data with a trend, relatively easy to use and have been tested fairly well [49]. The major difference between the NHPP and HPP is that the rate of occurrence with NHPP varies with time rather than being constant. For the remainder of this document, when reference is made to the ROCOF for NHPP, a time variant ROCOF is implied, which can be denoted $\rho(t)$. This is in contrast with the constant ROCOF ρ for the HPP.

Two formats of the NHPP found in literature is the log-linear NHPP, represented by

$$\rho_1(t) = e^{\alpha_0+\alpha_1 t}\text{, with } -\infty < \alpha_0, \alpha_1 < \infty, t \geq 0 \text{ [26][31]} \tag{9}$$

and the power law NHPP, represented by

$$\rho_2(t) = \lambda\beta t^{\beta-1}\text{, where } \lambda, \beta > 0, t \geq 0\text{. [26][31]} \tag{10}$$

NHPP repairable systems are best modelled with $\alpha_1>0$ (log-linear NHPP) and $\beta>1$ (power law NHPP), and a linearly increasing failure rate is obtained when $\beta=2$ (power law NHPP) [26]. System reliability, the expected number of failures and MTBF can be calculated from the NHPP models as shown in Table 2.4.

Table 2.4: NHPP equations for repairable systems for the interval (T_1,T_2) [26][31][49]

	Log-linear NHPP with $-\infty < \alpha_0, \alpha_1 < \infty, T_2 \geq T_1 \geq 0$	Power law NHPP with $\lambda, \beta > 0, T_2 \geq T_1 \geq 0$
Expected number of failures	$E_1(N(T_2) - N(T_1)) = \frac{1}{\alpha_1}(e^{\alpha_0+\alpha_1 T_2} - e^{\alpha_0+\alpha_1 T_1})$	$E_2(N(T_2) - N(T_1)) = \lambda(T_2^\beta - T_1^\beta)$
Reliability	$R_1(T_1,T_2) = e^{\frac{-(e^{\alpha_0+\alpha_1 T_2} - e^{\alpha_0+\alpha_1 T_1})}{\alpha_1}}$	$R_2(T_1,T_2) = e^{-\lambda(T_2^\beta - T_1^\beta)}$
MTBF	$MTBF_1(T_1,T_2) = \frac{\alpha_1(T_2-T_1)}{e^{\alpha_0+\alpha_1 T_2} - e^{\alpha_0+\alpha_1 T_1}}$	$MTBF_2(T_1,T_2) = \frac{T_2-T_1}{\lambda(T_2^\beta - T_1^\beta)}$

A practical framework for the analysis of failure data was discussed earlier, which suggests that failure data be tested for trends before a failure distribution can be fitted. With a trend present, the repairable systems approach should be followed, but it is important to understand that with no trend present, even repairable systems should follow the non-repairable approach.

2.4 Chapter Summary

Based on the literature on the statistical approach to failure analysis, the framework for the analysis of failure data can be adapted to include the methods explained in this chapter, and is shown in Figure 2.22.

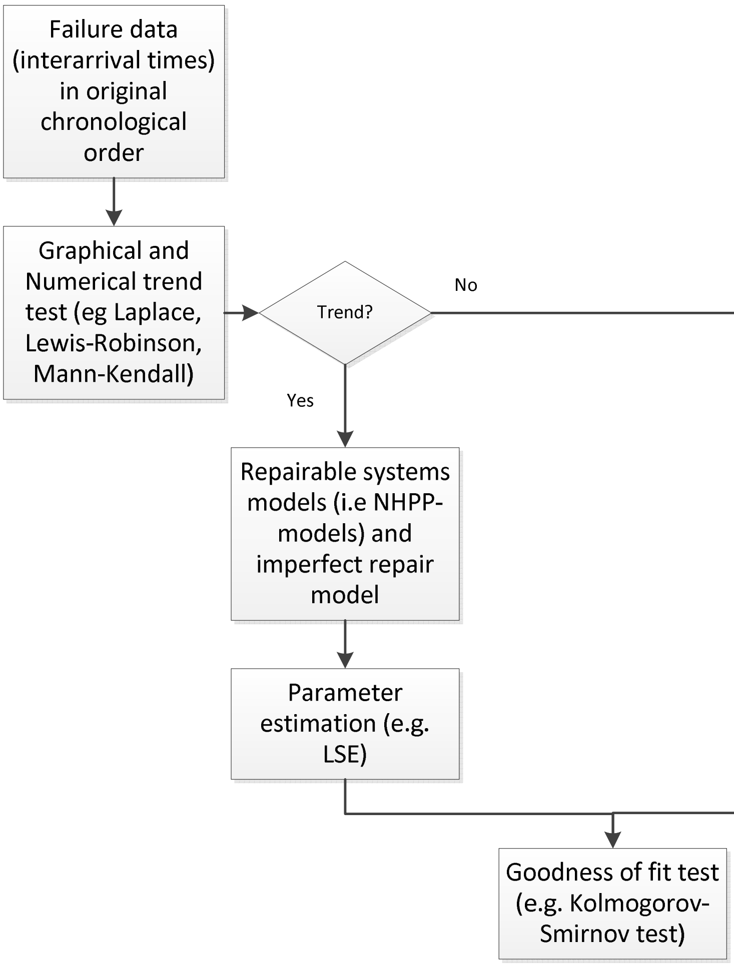


Figure 2.22: Summary framework for the analysis of failure data

3 APPLICATION OF RELIABILITY BASED MAINTENANCE MODEL

In the second chapter, the literature associated with the reliability of engineering assets was discussed. The application of the Reliability Based Maintenance (RBM) model is discussed in this chapter by means of a case study, applied to rolling stock at Metrorail. This chapter consists of four parts. The first part is a discussion of the methodology, followed by a discussion of reliability in the rail context, a sketch of the current maintenance situation at Metrorail while in the last part, the RBM model is applied at Metrorail.

3.1 Methodology for Modelling Reliability

The methodology for the Reliability Based Maintenance (RBM) model is presented, as summarised in **Error! Reference source not found.**. It consists of six steps starting with the literature review, and each step is discussed in more detail below.

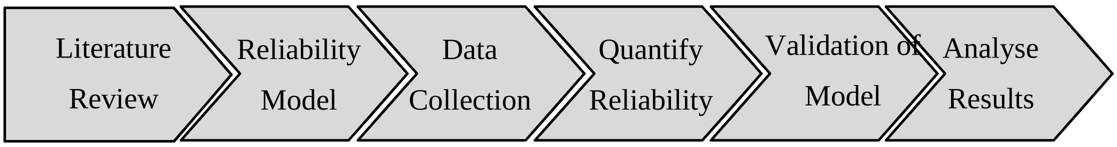


Figure 3.1: Methodology for the Reliability Based Maintenance model for quantifying reliability

Step 1: Literature Review

The first step is to understand the theory of reliability, the importance of measuring reliability and different techniques used in the quantification of reliability. The contribution of reliability in the AM context is defined, and the contribution of maintenance towards reliability is understood as well as the cost associated with reliability. Using statistics to model the reliability of a system is explained and graphical and numerical techniques investigated to explore trends in failure behaviour. Repairable and non-repairable systems are defined and the associated failure distributions discussed. The contribution of both components and sub-systems towards the reliability of sub-systems and systems respectively, are explained using RBDs, and redundancy.

Step 2: Reliability Model

The next step is to study the equipment and understand the interaction of the different systems. Critical or high risk components can be identified by performing a qualitative risk analysis on the main components of the different systems. A RBD model can then be constructed for these components showing their interaction. Care must be taken to balance the type of components in sub-systems, which will ensure that the reliability of sub-systems will not dominate the overall reliability of the system.

Redundancy must be taken into account and the number and sequence of operational components must be built into the RBD model.

Step 3: Data Collection

Once the RBD model is completed, failure data can be collected for the components. In this study the assumption was made that the replacement of components controls the condition of the system, ignoring any maintenance that is done in between the replacements. In addition, care must be taken in the interpretation of data in order to address the issue of truncated failure observations. In the case study, it was observed that data from the CMMS was not complete, and artificial “failures” were added at the beginning and/or the end of the observation period to make the failure pattern more realistic, as explained in Figure 2.19.

Step 4: Quantify Reliability

Here, the data is sorted and prepared for analysis. For each component in the RBD, the following four steps must be performed: 1) determine whether a trend is present using graphical and/or numerical methods, 2) determine the most appropriate failure behaviour, 3) calculate the parameters for the distribution, and 4) determine the goodness-of-fit for the parameters. Although there are many techniques which can be used during these four steps, only some techniques will be explained and used during the case study.

System reliability is then calculated using the failure behaviours of the different components simulated in the RBD model over time. All the data manipulation can be done in Data Microsoft® Excel, as proved in the case study

Step 5: Validation of model

The RBD model is validated using real data from Metrorail. For the purpose of the research and in order to prove the effectiveness of the model, three MCs with the most number of component failures are selected to validate the model. A train set is built using these three MCs and various failure behaviours tested.

Step 6: Analyse Results

The system reliability can then be analysed using different scenarios. By using the equations for the failure distributions, various calculations can be done like the prediction of failures, the calculation of MTBF or MTTF, the calculation of Reliability, residual life, cost optimisation and the effect of maintenance on reliability.

3.2 Reliability in the Rail Context

Many studies have been done on railway reliability and the effect thereof. These include studies on the relationship between reliability and productivity in railroad services [63], the importance of railway reliability to convince drivers of passenger vehicles to switch to public transport [64], the effect of unreliability on travel time [65], overcrowding because of delays and the effect thereof on productivity and efficiency of workers [66], and the effect of reliability on the availability of the service [42]. These studies clearly show that reliability is important to railroad companies and that the consequence of unreliability cannot be ignored.

Railway reliability can be measured in different ways among them the punctuality of the service [63], cancellations and delays [2] as well as the number of realised connections between trains [2]. From a passenger's perspective, the punctuality of the service is often used as a reliability measure, which is defined as the probability that the train will arrive at the final destination within a certain margin of the scheduled arrival time. Most of these reliability measures are lagging indicators and cannot be related to the source of the unreliability. The rail operator needs to carefully balance these measures because if one of them is overemphasised, the other measures might suffer and the commuter will be affected.

The average punctuality of some major European metro railroad operators is around 95% [67] where trains arrive at the final destination within the international margin of five minutes, although some operators use a three minute margin and still manage a punctuality of around 95%. In South Africa, the punctuality of the Metrorail railway system was 84% in 2011 [67] based on five minutes, which has room for improvement compared to international benchmarks.

In the literature review, various definitions of reliability were discussed. In the general definition of reliability, "the probability that an item will perform its intended function for a specific interval under stated conditions" [1], the *function* of rolling stock in the passenger rail context is to transport people to their destination on time, or simply *mission success*. From the rolling stock point of view, a successful mission can be defined as a train run completed without a failure of the asset.

It is clear that most reliability measures are based on the performance of the rail service and are lagging indicators, showing how well the assets were managed but which cannot be related to the source of the unreliability. A leading reliability measure is required, which must be forward looking and must assist with the performance management of the asset [43].

3.3 Current Reliability Strategy at Metrorail

In this section, the current maintenance strategy is discussed. The section starts with a short background of Metrorail followed by the current train set configuration and maintenance strategy at Metrorail.

3.3.1 Background of Metrorail

Metrorail is owned by PRASA and operates urban passenger trains in the four major metropolitans in South Africa [68]. With more than 270 train sets running over 2228km of track, Metrorail transport an estimated 1.7million paying passengers per weekday [69]. Metrorail operates an aging fleet of trains, some in operation since 1958. Metrorail predominantly uses cancellations and delays as a reliability measure for their fleet [67].

The first passenger coach arrived in South Africa in 1860, marking the start of passenger rail transport in the country. The first electric train was called the 2M and was commissioned in 1937 in Johannesburg. Since then, trains were constantly upgraded and every upgrade was given the next numerical number e.g. 3M, then 4M. Today, the fleet of 270 train sets consist predominantly of the 5M type (refer Figure 3.2, commissioned from 1959) as well the 8M, 10M2 and 10M3 types. The missing numbers (6M, 7M and 9M) were prototype trains and are not in use any more. Trains are maintained by Metrorail on a fortnightly basis while upgrades of trains are done every seven years by private companies.

Currently, PRASA is busy with modernisation programmes whereby 600 train sets will be procured and maintenance depots, infrastructure as well as stations will be upgraded. The introduction of new technology train sets is exciting but also challenging because the old rolling stock must still be operated, maintained and upgraded for another 15 years before it will be withdrawn from service. It is, therefore, important that the old fleet still be maintained to a high standard to maintain reliability and availability in order to minimise cancellations and delays.

3.3.2 Train Set Configuration

Metrorail defines a Motor Coach (MC) (Figure 3.2) as a powered rail vehicle able to transport passengers and to pull unpowered Passenger Trailers (PTs). A typical Metrorail train set consists of nine PTs and three MCs (one in the middle and one at each end). The contribution of PTs towards the reliability of a train set is insignificant compared to the contribution of the MCs. Thus, for the purpose of this study, the train set is represented by the three MCs only.

Figure 3.2: Typical 5M series MC

Three MCs are required for nine PTs to provide both enough tractive effort as well as system redundancy in the train set. Each MC is identical and the three MCs on a train set are inter-connected, whereby certain systems are connected in parallel creating spare capacity (called reducdancy). The compressed air system is one such system where the compressors on the three MCs are connected to the same piping system and air tanks, thereby compensating for the pressure drop over the length of the train set and allowing the pressure to build up faster. If one compressor fails, the train set will still be able to complete the mission normally and the compressor can be replaced at the next maintenance interval. If more than one compressor fail, then the train set will not be able to function normally and Breakdown Maintenance is required. The same applies for the vacuum system and 110V power supply system, where minimum two out of the three vacuum pumps (also called vacuum exhausters) and minimum two out of the three supply sets must be functional for the train set to be operational.

3.3.3 Current Maintenance Strategy of Metrorail

Metrorail maintains their own rolling stock fleet making use of CBM during planned intervals. During the late 1990's, a two week maintenance interval was adopted by Metrorail based on the average distance travelled per train set. This two week interval is still in use today and not adapted or changed according to the operational requirements. A train set is, therefore, scheduled for maintenance every two weeks, and the focus and intensity of maintenance will differ during each maintenance intervention. The question is whether the two week maintenance cycle results in over maintaining of the train sets thereby wasting valuable resources.

In Metrorail, there are three types of scheduled maintenance interventions (referred to as 'sheds'). A typical eight week maintenance cycle of any train set is summarised in Table 3.1.

Table 3.1: Three types of maintenance activities, spread over an eight week cycle at PRASA

Week number	**Shed name**	**Description**	**PRASA reference document**
Week 0			
Week 2	A-Shed	Passenger Safety and Comfort (PS&C)	DOCS_MHQ-#71498-V5-A_SHED_-_ELECTRICAL_FITTER_CHECK_SHEET
Week 4	B-Shed	Intermediate Shed	DOCS_MHQ-#87635-V1-B_SHED_-_ELECTRICAL_FITTER_CHECK_SHEET
Week 6	A-Shed	PS&C Shed	
Week 8	C-Shed	Full Shed	DOCS_MHQ-#71514-V3-C_SHED_-_ELECTRICAL_FITTER_CHECK_SHEET

The Railway Safety Regulator (RSR), who is the custodian of railway safety in South Africa, requires that passenger and safety inspections are done regularly on each train set, which is two weeks in the case of Metrorail. During the A-Shed, the main focus is the safety and comfort of the passengers, focussing on the functionality of components such as the braking system, wipers, doors, horn, etc. The majority of the maintenance activities do not add value to the reliability of the train set, hence the name *safety and comfort*.

During a B- and C-Shed, CBM is applied to various components over and above the activities from the A-Shed. For CBM to be effective, components are classified in terms of condition. A condition of five indicated a new component, a condition of two means that the component must be replaced at the next maintenance intervention, and a condition of one means that the train set must be removed from service and the component replaced immediately. CBM is applied to components such as [3]:

- Traction motors
- Compressors
- 110V Supply sets
- Exhausters
- Static invertors
- Pantographs
- Wheels

The condition of these components are categorised during CBM and captured on checklists and on the Facility Maintenance Management System (FMMS), which is then used to plan TdM interventions based on the conditions equal to two. Unfortunately, the criteria used for the classification of these components are not clear and not conclusive to make a confident classification, which leads to questioning of CBM effectiveness.

3.4 Reliability Based Maintenance Model Applied to Metrorail

In this section, the application of the RBM model is explained. It describes where the data was obtained from and how the failure data was manipulated and interpreted in terms of system reliability.

3.4.1 Collection of Data

In order to effectively quantify the reliability of rail rolling stock, the contribution of component failures to cancellations and delays was investigated and the critical components identified. Failure data, which was obtained from the FMMS, was analysed and the three most critical MCs were identified for further calculations.

3.4.1.1 Identification of Critical Components

In a study done by the author (refer to Appendix F), the contribution of different components in a MC towards cancellations and delays were investigated. The components can be classified in different groups, which can be seen in the first column of Table 3.2. The grouping was done by Metrorail many years ago to make the analysis of the contribution of components towards cancellations and delays easier.

It is clear that group E is a significant contributor to cancellations and delays, and that the *Time per delay* and *Time per event* in columns II and III are less than the other groups. *Time per delay* refers to the average time of train delays while *Time per event* refers to the time it took to close the fault. After further investigation, it can be reported that group E consists of all electronic components like electronic boards, circuit breakers, master controller, instruments, lights, etc. Many faults on these components can be repaired by either resetting the system, or the quick replacement or repair of the component. The electronic components from this group are integrated into the other groups, and failure of many electronic components have an influence on system functionality. Unfortunately accurate failure data are not recorded for this group and therefore this group, although important for functionality, will not be considered for the simplified reliability model in this research.

Group M (Traction and Auxiliary machines and controls) was used in this study as this group contributes 14% to delays and 13% to cancellations. This group is significant compared to the other groups and plays a major role in the reliability of the rolling stock fleet.

Table 3.2: Contribution of component groups to cancellations and delays [67]

Group	Group description	Contribution to delays Column I	Time per delay Column II	Time per event Column III	Contribution to Cancellations Column IV
E	Electronic Control Equipment	47%	18.0 min	44.3min	31%
P	High Voltage and switch equipment	23%	18.4 min	50.4 min	30%
M	Traction/Auxiliary machine and controls	14%	19.3 min	52.2 min	13%
O	Brake gear	2%	17.5 min	29.7 min	5%
B	Cab and Saloon doors	6%	21.1 min	46.5 min	6%
A	Air related	4%	18.1 min	58.6 min	4%
G	Pantograph	3%	18.9 min	54.0 min	7%
	Other components	1%	13.9 min	20.5 min	4%
			18 min ave	**46 min ave**	

The focus of this study is on the *position* of the components in a MC, earlier defined as a socket [31], which is “a space that at any given time, holds a part of a given type” [29]. The major components in group M are repairable components, thus, when any these components fail in a MC, it will be removed and sent to the repair shop while another will be drawn from stock and fitted.

The risks of the major components in group M were determined using a qualitative risk analysis. In order to demonstrate the analysis, a probability-consequence analysis was done on the major components in group M using values obtained from experts at Metrorail. The probability and consequence of the four major components in this group are shown in Figure 3.3 together with other components of a MC for comparison. The four major components in group M are (abbreviations shown in brackets):

1. Traction motor (TM).
2. Compressor (COMP).
3. 110V Supply set (SUPPLY).
4. Vacuum Exhauster (EXH).

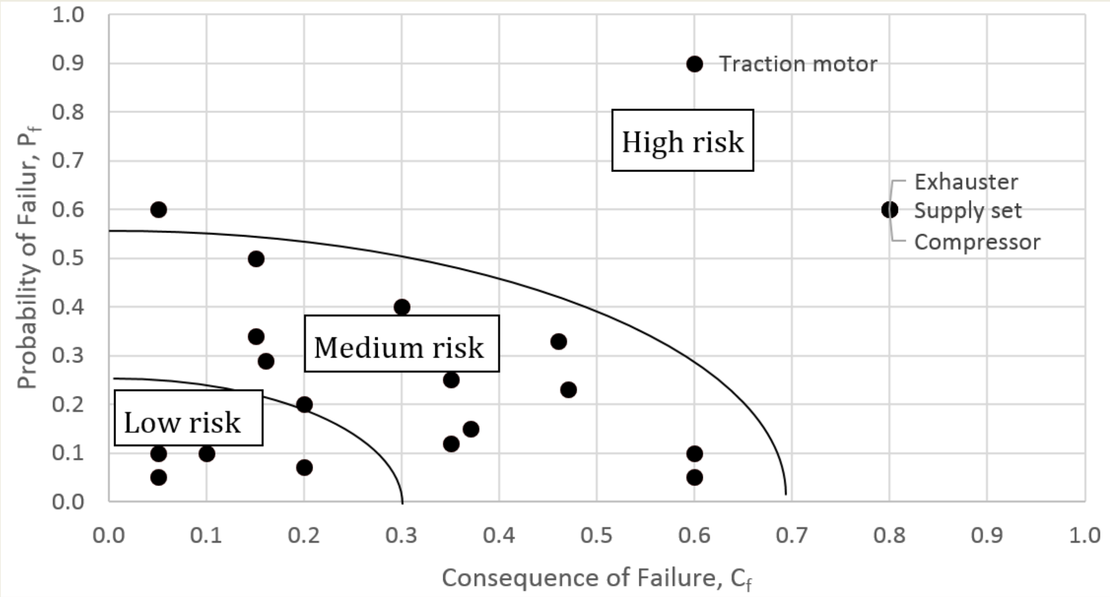


Figure 3.3: Qualitative risk analysis for selecting critical components

The probability of failure (P_f) of the TM is higher than that of the other components (Figure 3.3), but the consequence of failure (C_f) of a TM is lower than a supply set, compressor and vacuum exhauster. The C_f of a TM is less than the other components because there are four TMs on a MC working in a specific configuration. This will be illustrated in section 3.4.3.1, where the RBDs are shown.

Parallels between these four components are that:

- each component is the main component of a sub-system, i.e.
    - the compressor, which includes an electrical motor and pump, generates compressed air for the air system.
    - the traction motor is the most critical component in the propulsion system.
    - the vacuum exhauster, which includes an electrical motor and vacuum pump, is the main component in the vacuum system.
    - the supply set, which includes an electric motor and alternator, is the main component in the 110V supply system.
- the components are driven by an electric motor or are electric motor itself.
- these four components combined contribute 14% to delays and 13% to cancellations of rolling stock at Metrorail [67].
- these components are serialised, repaired by Metrorail and failure data is available.

3.4.1.2 Identification of Critical MCs

For the purpose of this study, three MCs were selected with the worst failure data during the observation period, which will be used for the duration of this study. Ten MCs with the most number of failures were identified and the number of failures for each component are listed in Table 3.3. The contribution of each component to reliability was taken from Figure 3.3 (C_f) and is indicated in the row marked *Weight* in Table 3.3.

Table 3.3: Selecting the three worst Motor Coaches using weighted average method

		Number of Replacements				Weighted Priority	MC reference
		SUPPLY	EXH	TM	COMP		
	Weight	0.8	0.8	0.6	0.8		
Coach number	17673	4	6	23	6	26.6	MC3
	19605	4	5	22	6	25.2	MC2
	17653	3	13	19		24.2	MC1
	13128	5	6	22	2	23.6	
	17655	1	5	25	4	23.0	
	17633	3	9	18	2	22.0	
	19602	2	5	20	5	21.6	
	13232	11	4	13		19.8	
	13032	8	7	8		16.8	
	13021	6	3	9	4	15.8	

The three worst MCs were identified based on the number of failures using the weighted average method. The three MCs are MC17653, MC19605 and MC17673. For the remainder of this study, these MCs are numbered MC1, MC2 and MC3 respectively, as indicated in Table 3.3.

3.4.1.3 Data Mining

As mentioned, Metrorail captures all maintenance and inspection information on a FMMS database. The system uses a Structured Query Language (SQL) based program to obtain information from the FMMS database, called GQL (General Query Language).

A GQL query was created and used to obtain data from the FMMS, focussing on the replacement of the four listed components [70]. For the purpose of this study, the following assumptions were made:

- That the replacement of a component will be regarded as a failure.
- That the maintenance activities between replacements will be ignored.
- That the contribution of scheduled maintenance (between replacements) is insignificant.
- That replacements of the selected four components are representing the behaviour of the MC.
- That the data from the FMMS can be trusted and represent the real situation, although Metrorail reported that the FMMS was not operating at times.

Failure data from 18 March 2003 until 12 August 2013 was used, representing nearly 200 MCs of the 5M type train. Within this period, 2947 traction motors, 555 supply sets, 587 vacuum exhausters and 174 compressors were replaced.

A typical dataset from FMMS is shown in Table 6.6 in Appendix D, from which it can be seen that:

- Components are serialised.
- The data only focuses on Removal and Replacement (R&R) of components.
- A job description of the fault symptom is included.
- Each component can be uniquely identified by means of a serial number.
- The socket can be uniquely identified by referencing (e.g. 13120.BOG2_TM3 refers to MC number 13120, Bogie number 2, traction motor 3).

With reference to Figure 3.4, where the failures for the four listed components are shown over the ten year observation period, it can be seen that the number of TM replacements far exceeds the other components. Here, a direct assumption could be made that this is the most critical component on a MC. However, it must be kept in mind that there are four TMs on a MC and only one pair of TMs is required to be functional (as shall be discussed in a later section), but there is only one supply set in a MC, one compressor and one vacuum exhauster.

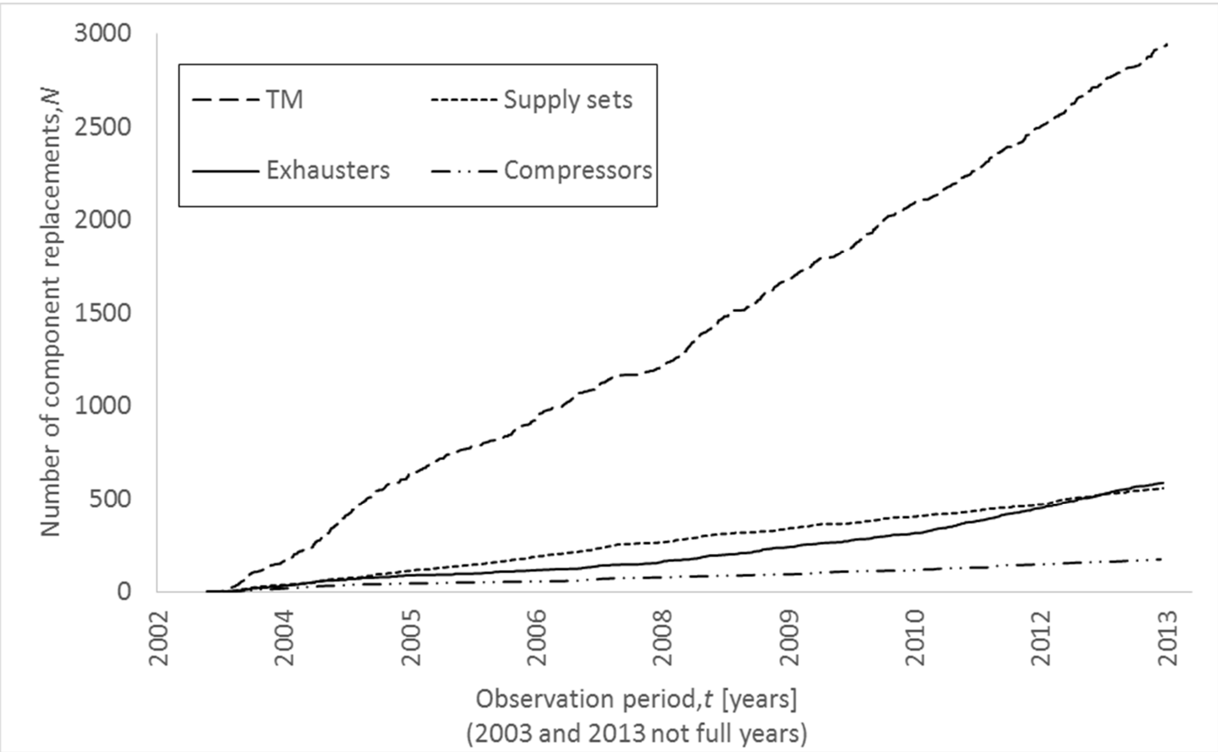


Figure 3.4: Rate of Occurrence of Failure plot for all components on all MCs

3.4.2 Failure Analysis of Components

This section will illustrate how the statistical techniques, discussed in the literature review, will be applied to model the failure behaviour of the components. The techniques were applied to all the components in the three selected MCs (MC1, MC2 and MC3), but only the TMs and later TM3 of MC3 will be discussed for illustration purposes. The results from the trend tests as well as the failure behaviour parameters can be found in Appendix E.

The failure data of the TMs was analysed and failure models determined for:

- The TMs for the total population where the aim is to sketch the broader picture of the TM failure behaviour.
- The TM of each of the three selected MCs.

The analysis of TM3 of MC3 will be discussed in detail as it was one of the few components where all three trend tests were required before a conclusion of a trend could be made.

3.4.2.1 TM Failures for the Fleet of MCs

A graphical assessment of the failure behaviour was done for all the TMs combined, where after a failure mode analysis (as part of RCM) was done for illustration purposes on all the TMs followed by a detailed analysis of all the armature failures. There were 2947 TM failures recorded during the observation period and the spread over the ten years observation period is shown in Figure 3.5. The failures for 2003 and 2013 were not recorded for the full year, therefore the significant lower values for those years.

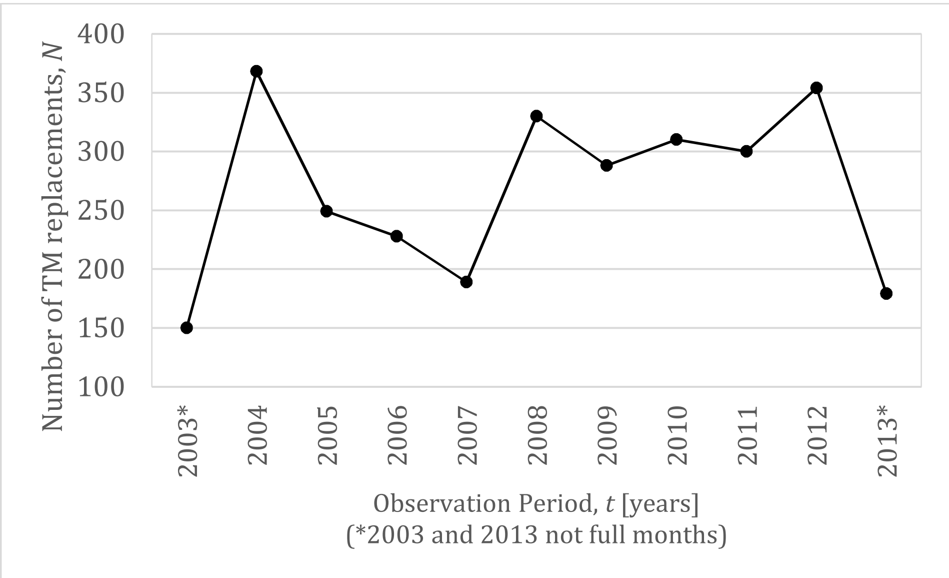


Figure 3.5: Yearly number of TM replacements from 2003 to 2013

By visually inspection of the ROCOF graph and focussing on the gradient of the TM failures (Figure 3.4), it can be seen that the gradient is fairly constant and the failure points are in a straight line. With such a straight line, a conclusion cannot be drawn as to whether the failures have a trend or not. The graphical assessment reveals a *random* failure rate, as discussed in section 2.3.3.1.

Thus, a quantitative analysis is then done to confirm the outcome of the graphical assessment, and the LTT is used to calculate the value of U_L :

$$U_L = \frac{\frac{1}{r-1}\sum_{i=1}^{r-1} T_i - \frac{T_r}{2}}{T_r\left[\frac{1}{12(r-1)}\right]^{\frac{1}{2}}}$$

where r=2946,

T_r=3800, and

T_i=0;71,73,78;79 ……… ,3800

$$= \frac{(\frac{1}{2946-1})(\sum_{i=1}^{2946} T_i - \frac{3800}{2})}{3800\left[\frac{1}{12(2946-1)}\right]^{\frac{1}{2}}}$$

$$= 4.529$$

From the calculation, it can be seen that U_L is higher than the upper limit (U_L >2) and the failures of all the TMs combined show strong indication of reliability degradation, which does not correlate with the result of the graphical assessment. A possible reason for this mismatch can be that it is more difficult to see a trend with so many data points (2947 points) because of the limitations of scaling of the graph. The failures data is, therefore, non-homogeneous and the repairable system theory applies.

The Pareto graph for all TM failure modes is shown in Figure 3.6. The failure mode information was obtained from the GQL report from which it can be clearly seen that defective armatures contribute 45% to the total number of TM failures. This is significant given that the 892 armature failures represent nearly half of the total number of TM failures. Furthermore, it can be seen that four failure modes (Armature Defective, Commutator Worn, Low Megger Reading, and Fields Earthed) contribute nearly 80% of the failures on TMs. Most of these failure modes cannot be prevented with traditional PM techniques (like CBM), which then calls for predictive models like statistical analysis.

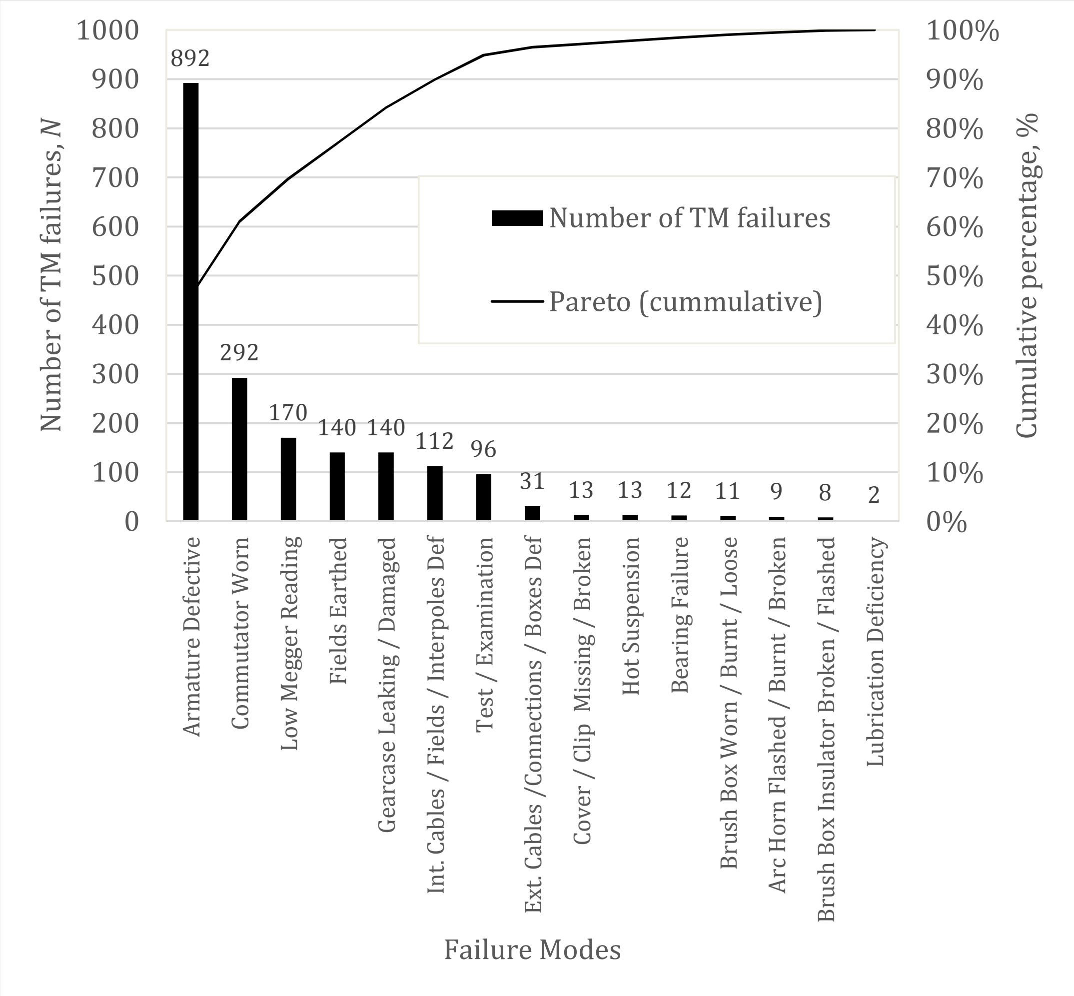


Figure 3.6: Pareto graph for all TM failure modes

From the total number of failures, the inter-arrival events are identified. This reduced the list of failures from 2947 to 1001, with the reason for this significant lower number of inter-arrival events being that the first failure of every specific TM was disregarded, and only the inter-arrival times between consecutive failures could be used. Many TMs failed only once, which means that such failure was disregarded when calculating inter-arrival times.

A histogram of the 1001 failures is created to understand how soon after replacement the failures occur, which is then compared to the expected life of two years, as recommended by De Wet [71]. Figure 3.7 summarises these failures and the following can be highlighted:

- 5 TMs (0.5%) failed within 1 day after replacement.
- 17% TMs failed before 100 days, 24% before 200 days and 34% before 300 days.
- 39% of TMs fail before the warrantee period of one year [71].
- 59% of TMs fail before the expected two year lifespan.
- 80% of TMs fail before 1400 days.

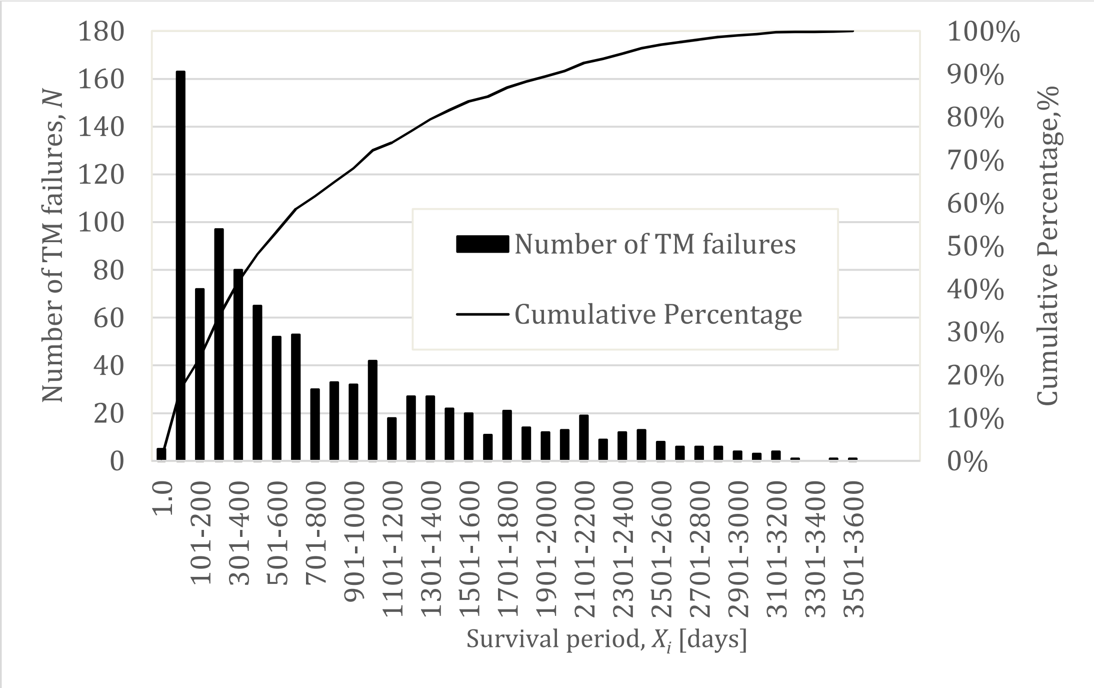


Figure 3.7: Histogram for all TM failures on all MCs

This clearly shows an infant mortality failure pattern, which indicates that this analysis can be used to plan effective PM interventions. A further analysis for each failure mode can be done in order to understand which failure mode contributes the most to infant mortality. This is, however, not within the scope of this study, so it will not be discussed further.

3.4.2.2 TM3 Failures of MC3

For illustration, only the calculations done to determine the failure behaviour of TM3 on MC3 is shown, where the inter-arrival and arrival times for TM3 are shown in Table 3.4. The failure behaviour for the other components were calculated using the same method.

Table 3.4: Inter-arrival times and arrival times for TM3 on MC3

Failure	Inter-arrival times, days (X_i)	Arrival times, days (T_i)	Failure truncated (C_i=0) or real (C_i=1)
1	882	882	0
2	434	1316	1
3	1946	3262	1
4	112	3374	1
5	44	3418	1
6	383	3800	0

3.4.2.2.1 Graphical Assessment of the Failure Behaviour for TM3

The graphical procedures, as defined by Ascher and Feingold [29], will be used in the TM3 example, where it will be shown whether the system is deteriorating or improving:

1. Plotting cumulative failures versus cumulative time on linear paper.

   In this plot, the number of cumulative failures are plotted against the cumulative time in a linear scale. The ROCOF graph for TM3 on MC3 is shown in Figure 3.8, where two distinct periods are visible:

   Period 1: point 1 to 3, steady reliability growth can be observed.

   Period 2: point 3 to 6, deterioration period.

   From the visual assessment, it is inconclusive whether the system is deteriorating, improving or constant. Looking at the periods separately, it can be argued that period 1 shows reliability improvement while period 2 shows reliability degradation. It is, however, not possible to come to a definite overall conclusion with the graphical assessment alone.

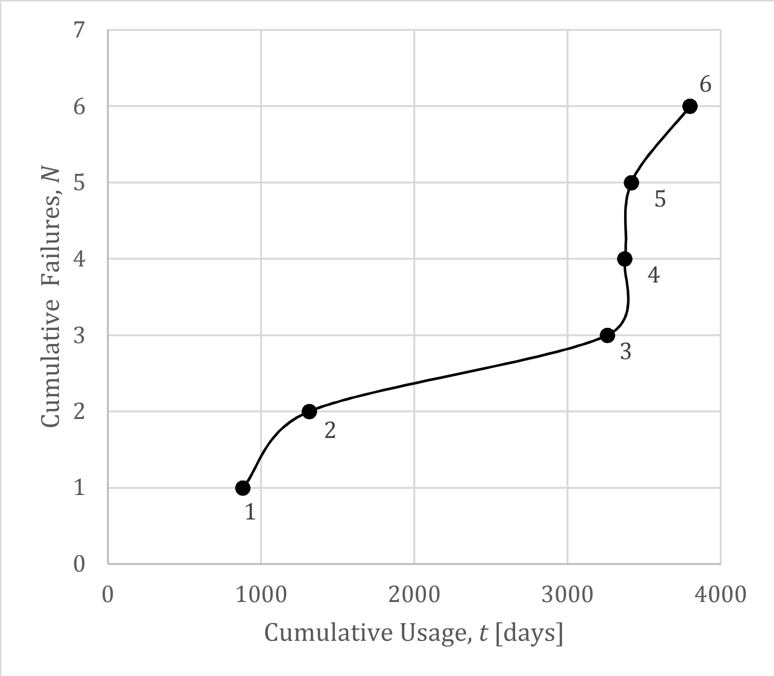


Figure 3.8: ROCOF graph for TM3 failures on MC3

2. Estimating average ROCOF in successive time periods.

   The average ROCOF method, as discussed by Ascher and Feingold [29], will now be illustrated. The observation period is split into 2 subintervals of 1900 days each ($n=2$, $\Delta t=1900$), and the number of failures in the successive subintervals are calculated as $v_1=2$ and $v_2=4$. In the first subinterval (v_1), the sum of the inter-arrival times of the first two failures is less than Δt (X_1+X_2=1316), and the sum of the last four observations fall in the second subinterval.

   Proper conclusions cannot be made with a low number of subintervals, thus, in order to investigate the shortcoming of this procedure, the subintervals are increased to 10 ($n=10$). The results for the different subintervals are reported in Table 3.5 and graphically shown in Figure 3.9 for $n=8,9,10$.

Table 3.5: Graphical Calculation of average ROCOF for TM3

Number of Subintervals, *n*	**Interval length, Δt [days]**	**Number of failures in subinterval**									
		v_1	v_2	v_3	v_4	v_5	v_6	v_7	v_8	v_9	v_{10}
10	380	0	0	1	1	0	0	0	0	3	1
9	422	0	0	1	1	0	0	0	2	2	
8	475	0	1	1	0	0	0	1	3		
7	543	0	1	1	0	0	0	4			
6	633	0	1	1	0	0	4				
5	760	0	2	0	0	4					
4	950	1	1	0	4						
3	1266	1	1	4							
2	1900	2	4								

It can be seen in Figure 3.9, that there seems to be constant ROCOF during the first 2 failures, followed by a sharp drop-off in ROCOF caused by the relatively long third inter-arrival time. The ROCOF increase sharply towards the end of the observation period and the shortcoming of the procedure can be seen when the graph for n=*9* appears to become constant, while the graph for n=8 still shows an increased ROCOF and the graph for n=10 shows a declining ROCOF.

The emphasis here is that the choice for the subinterval length is important and can influence the result of the graphical technique drastically. Care must, therefore, be taken when using this graphical technique in isolation.

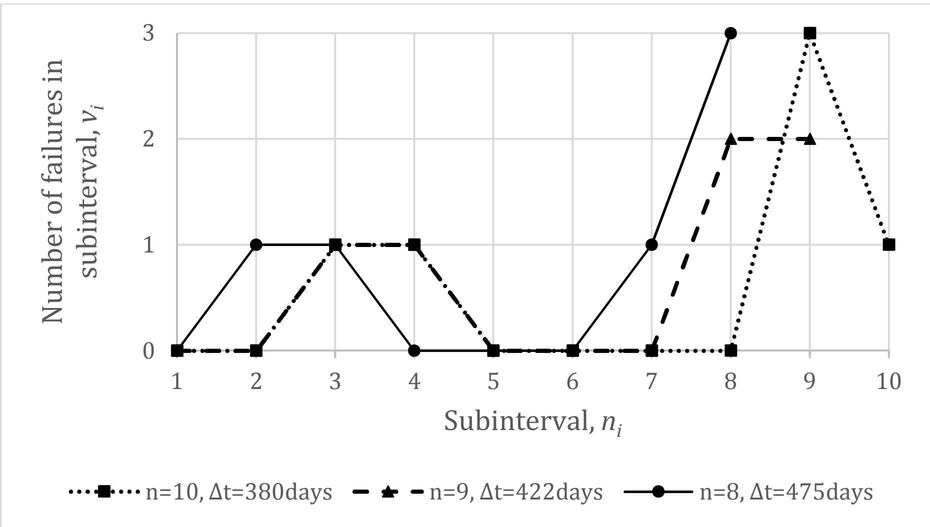


Figure 3.9: Average ROCOFs for TM3 for different number of subintervals

3. Duane plot.

   The Duane [51] plot was done on a log-log scale, according to the literature review, and the results can be seen in Figure 3.10. The straight line can be observed but it must be reported that it did not add value towards the interpretation of the failure trend of TM3 in this case. The Duane plot however contributed to the understanding of the failure trend of other components, like the TM4 of MC2.

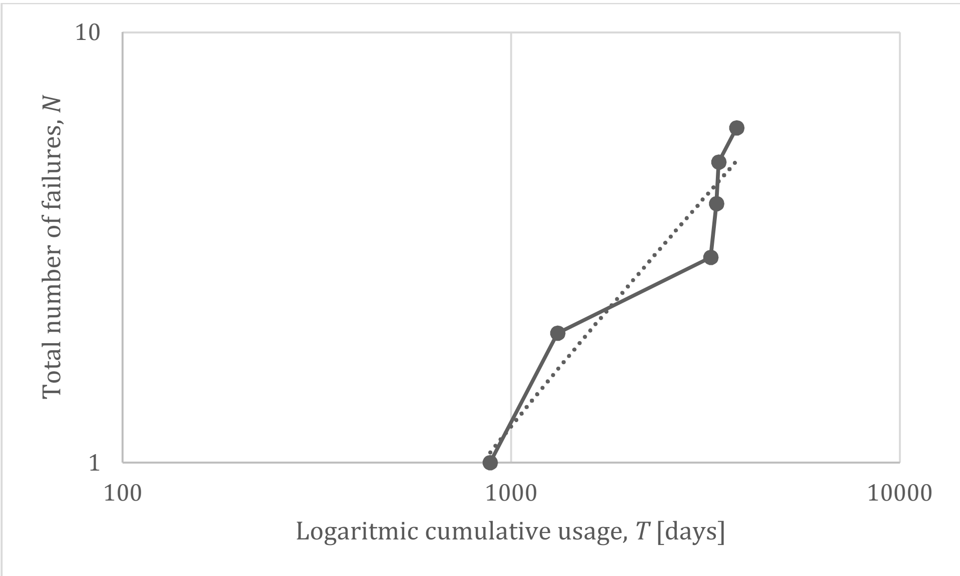


Figure 3.10: Duane [51] plot for TM3

3.4.2.2.2 Calculating the Failure Trend for TM3

With the graphical assessment inconclusive, the LTT is used to calculate the value of U_L for TM3 on MC3 with equation (4). From the arrival times in Table 3.4, the U_L is calculated as follows:

$$U_L = \frac{\frac{1}{r-1}\sum_{i=1}^{r-1} T_i - \frac{T_r}{2}}{T_r\left[\frac{1}{12(r-1)}\right]^{\frac{1}{2}}}$$

where r=6,

T_r=3800, and

T_i=881,67; 1315,5; 3261,5; 3373,5; 3417,5; 3800.

$$= \frac{(\frac{1}{6-1})(\sum_{i=1}^{5} T_i - \frac{3800}{2})}{3800\left[\frac{1}{12(6-1)}\right]^{\frac{1}{2}}}$$

$$= 1.730$$

The U_L value falls within the grey area, as 1< U_L <2, thus, either the renewal theory or repairable systems theory can be applied. Therefore, the L-R test is performed as follows using equation (5):

$$U_{LR} = \frac{U_L}{CV}$$
$$= \frac{U_L}{(\frac{\sqrt{Var[X]}}{\overline{X}})} \text{ with } CV[X] = \frac{\sqrt{Var[X]}}{\overline{X}} \text{ and } \sqrt{Var[X]} = \text{the standard deviation}$$
$$= \frac{1.730}{(\frac{708.04}{633.33})}$$
$$= 1.590$$

Like the LTT, the L-R test result is also in the grey area, so the MK test is performed next. For simplicity, the calculation of equation (6) is shown in the Table 3.6:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \mathrm{sgn}(x_j - x_i) \tag{6}$$

Table 3.6: Mann-Kendall calculation for TM3 in MC3

	Event 1	Event 2	Event 3	Event 4	Event 5	Event 6	Sum of rows
Inter-arrival times	881.67	433.83	1946	112	44	382.5	
Compare to Event 1		-1	1	-1	-1	-1	-3
Compare to Event 2			1	-1	-1	-1	-2
Compare to Event 3				-1	-1	-1	-3
Compare to Event 4					-1	1	0
Compare to Event 5						1	1
						S=	**-7**

From Table 6.2 in Appendix B, the MK value is 0.136, using n=6 and S=-7, if α equals 0.05. The *MK* of 0.136 is the probability of obtaining an S-value equal to 7 or larger, when *n*=6 and no upward trend is present. Since the *MK* value is more than α and S is negative, H_0 of no trend cannot be rejected.

It can, therefore, be concluded from the MK test that there is no trend in the failure data with an 86.4% confidence factor. It can also be concluded that, although the TM is a repairable component, it will be treated as a non-repairable because there was no trend.

3.4.2.2.3 Parameter Estimation for TM3

The trend tests suggested that there is no trend in the TM3 failure data. Therefore, the failure arrival times are i.i.d. and conventional analysis techniques can be followed. It was mentioned in the literature review, that the Weibull is one of the most widely used and flexible lifetime distributions [60]. Thus, the Weibull distribution was used to model the failure behaviour for TM3.

The data was prepared for linear regression, and the results are listed in Table 3.6. The complete linear regression results can be seen in Table 6.5 of Appendix C, where the coefficients in the regression results are used to calculate the Weibull parameters, as shown below.

Table 3.7: Table for parameter estimation for TM3 on MC3

X	Rank order	Median Rank	1/(1-Median Rank)	ln(ln(1/(1-Median Rank))).	ln(X)
44	1	0.109	1.122	-2.155	3.784
112	2	0.265	1.361	-1.175	4.718
382.5	3	0.421	1.729	-0.601	5.946
433.83	4	0.578	2.370	-0.147	6.072
881.67	5	0.734	3.764	0.281	6.781
1946	6	0.890	9.142	0.794	7.573

From the equations in Table 2.3 and the linear regression coefficients in Table 3.8, the Weibull parameters can be calculated as:

$$\beta = \text{"X Variable1"} = 0.764$$

$$\eta = e^{-(\frac{c}{\beta})} = e^{-(\frac{\text{"Intercept"}}{\beta})} = e^{-(\frac{-4.943}{0.764})} = 644.141$$

Table 3.8: Linear regression coefficients for the calculation of the Weibull parameters for TM3

	Coefficients
Intercept	-4.94294
X Variable 1	0.764224

The reliability of TM3 on MC3 can, therefore, be modelled in terms of its failure behaviour as follows:

$$R(x) = e^{-(\frac{x}{\eta})^{\beta}} = e^{-(\frac{x}{644.141})^{0.764}}$$

3.4.2.2.4 KS Goodness-of-Fit Test for TM3

From the calculated Weibull parameters, the KS goodness-of-fit test is done for TM3 on MC3 to ensure that the confidence of the parameters is within specified significance levels. For the purpose of the KS test, S_n is defined by the Weibull failure function as:

$$S_n(t) = 1 - e^{-(\frac{t}{\eta})^{\beta}}$$

With six observations and a significant level (α) of 5%, the d value of 0.521 was obtained from Table 6.3 in Appendix B. The results show that $S_n(t)$ is not a good fit, based on equation (7) for the first data point:

$$F_0(t) - d_\alpha(N) < S_n(t) > F_0(t) + d_\alpha(N)$$
$$0.166 - 0.521 < 0.719 > 0.166 + 0.521$$
$$0 < 0.719 > 0.6877$$

Therefore, the hypothesis that $S_n(t)$ fits $F_0(t)$ will be rejected. The Weibull parameters are recalculated as follows:

- Old Weibull parameters: η=644.14, β=0.764
- New Weibull parameters : η=722.15, β =0.764

The KS test result based on the recalculated Weibull parameters is shown in Figure 3.11.

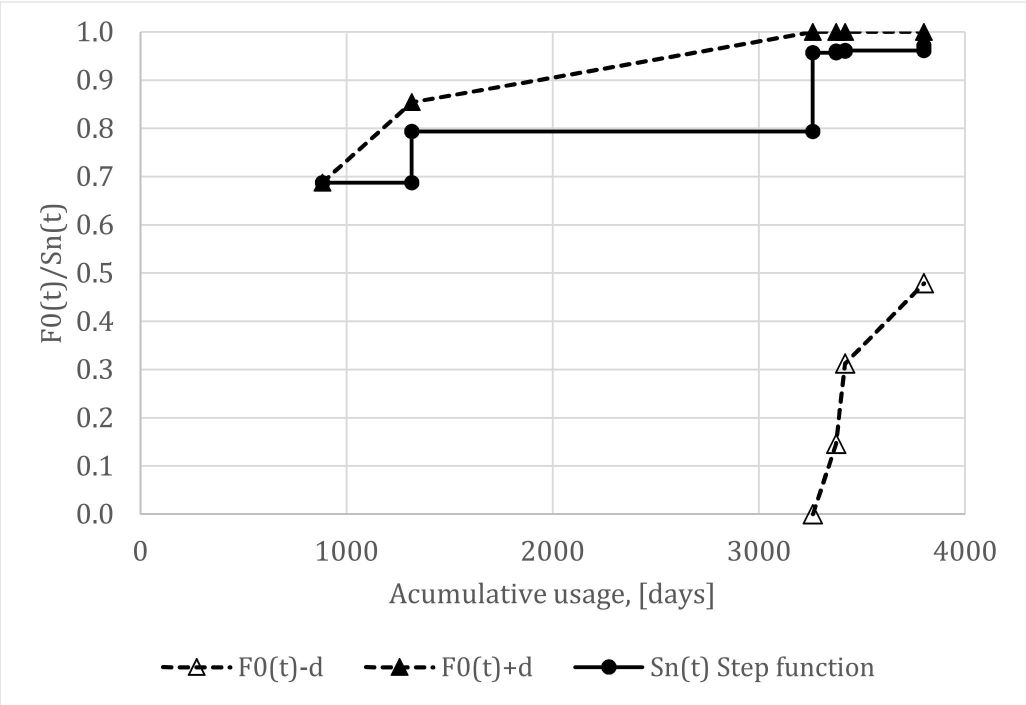


Figure 3.11: KS test result for TM3

3.4.3 Failure Analysis of MCs

For an effective failure analysis of the MCs, a RBD was constructed and the failure behaviour determined for each component. The failure analysis, as discussed in section 3.4.2, is applied to all the components and the results are reported in Appendix E. In this section, the methodology followed for the failure analysis of the MCs is discussed.

3.4.3.1 RBD Models for Rolling Stock

Once the logic of the sub-systems of a MC is understood, a RBD can be constructed and the failure characteristics of the different components can be calculated. A MC consists of various sub-systems, configured in series and parallel. Although the sub-systems are constituted of several components, a basic model was constructed demonstrating the interaction of the four different sub-systems. As mentioned, the approach in this study is to construct a basic model where each sub-system is represented by a single component, as reflected in section 3.4.1.1.

The details of the selected sub-systems is listed in Table 3.9, and the number of components required to survive in either a MC or a train set configuration is indicated. The RBD of a MC is shown in Figure 3.12, which shows the inter relationship of the components and the redundancy.

Table 3.9: Description of main components and systems of a MC

			Number required to survive	
Sub-system	**Component**	**Abbreviation**	**MC**	**Train set**
Power generation	Supply set	SUPPLY	1/1	2/3
Compressed air	Compressor	COMP	1/1	2/3
Vacuum system	Vacuum exhauster	EXH	1/1	2/3
Propulsion system	Traction motor	TM	2/4	6/12

Most of the four components on a MC are connected in series, with redundancy only in the propulsion system. The propulsion system consists of four TMs and is best described by a *balanced k-out-of-n* system represented by a series-parallel system, where each bogie on the MC is represented by two TMs in series and the bogies connected in parallel. A MC needs to have at least two TMs operating in series, which means that the failure of one TM will shut down the other TM on the same bogie but the MC will still operate. If another TM will fail in this failed state, the last TM will also be shut down and the MC will not operate.

By making use of equations (1) and (2) and with individual reliabilities for each component, the reliability of the TM sub-system can be calculated as follows:

$$
\begin{aligned}
R &= 1-\prod_{i=1}^{n}(1-\prod_{j=1}^{m} R_i) \\
&= 1-\prod_{i=1}^{2}(1-\prod_{j=1}^{2} R_i) \\
&= 1-(1-R_1R_2)(1-R_3R_4)
\end{aligned}
$$

where R=Overall Reliability, R_1=Reliability of TM_1, R_2 = Reliability of TM_2, etc.

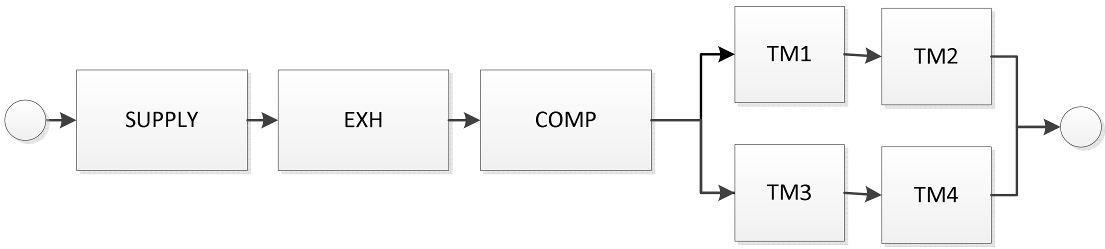


Figure 3.12: Simplified RBD for a MC

3.4.3.2 Analysis of the Failure Trends for MCs

The failure data for the selected MCs were analysed and a graphical assessment done to determine trends in the failure data (refer to Figure 3.13). In the literature review, the use of the ROCOF was explained and this is now illustrated for the three MCs.

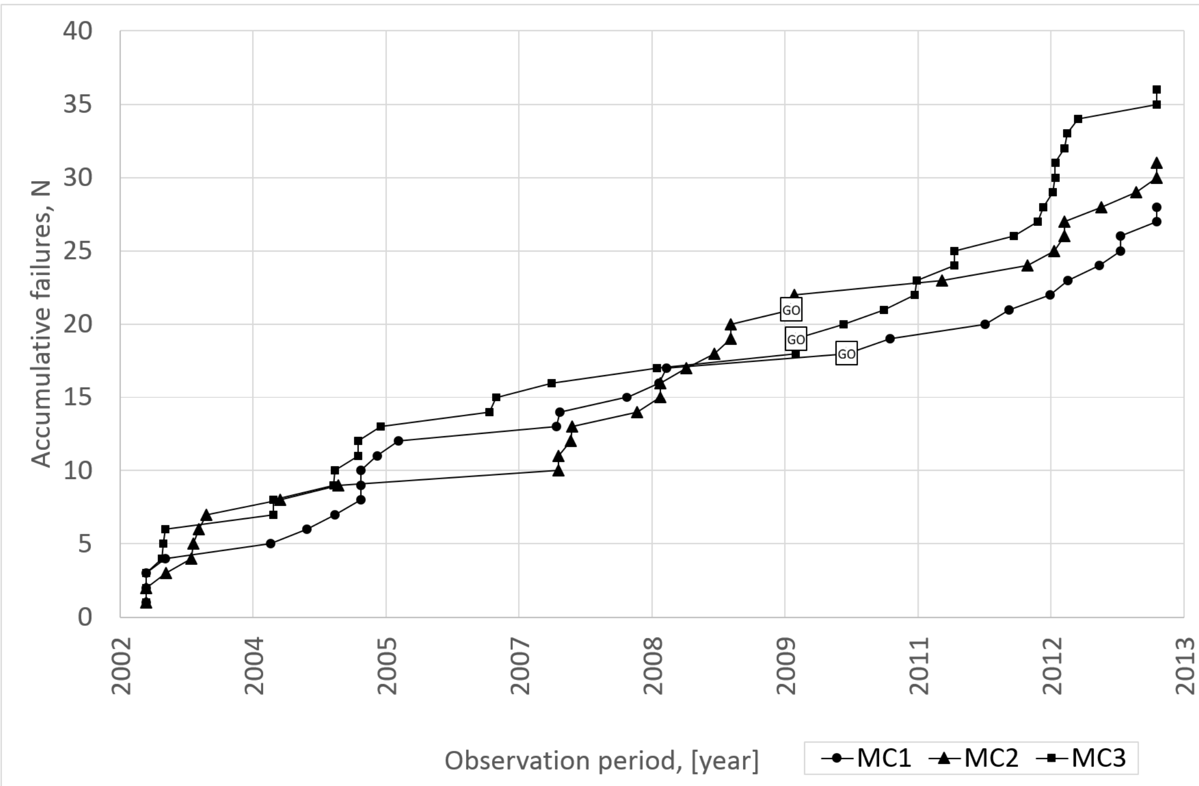


Figure 3.13: ROCOF plot for all component failures on MC1, MC2 and MC3

In Figure 3.13, the combined failures of the four components (TM, COMP, SUPPLY and EXH) are shown for the observation period from 2003 until 2013. During the observation period, all three MCs were overhauled, which is indicated in Figure 3.13 as *GO (General Overhauled)*.

At first glance, the overall trend looks similar for the three MCs, but there are fundamental differences during different periods. Initially, MC2 had seven failures in quick succession followed by three failures at a lower rate until the middle of 2007. During the same period, MC1 had 14 failures and MC3 had 17 failures. During the last period, the failure rate was generally higher for the three MCs, with MC1 and MC2 showing a similar failure trend since the beginning of 2012 and had 8 failures each, while MC3 had 13 failures in the same period. The overall results tend towards a straight line indicating random failures, therefore no trend.

The results of a LTT on each MC show that the data is non-committal and no trend present, as shown in Table 3.10.

Table 3.10: LTT results for the three MCs

	MC1	**MC2**	**MC3**
LTT value (U_L)	0.14	0.02	0.47

The impact of the *GOs* on the failure trends must be highlighted, where it can be seen that the failure rate of MC2 was significantly lower after the *GO*, but the failure rate of MC1 and MC3 either steadily increased or was significantly higher after the *GO*. It turned out that the *GOs* on MC1 and MC3 were done by the same supplier and it must be questioned whether the GO contributed to reliability as expected.

The danger associated with using the MTBF without taking the chronological order of the failures into account, was discussed in section 2.3.3. It can be seen, from the discussion above, that the failure rates for the MCs are different for the different time periods. The LTT shows no trend but when the time periods are isolated, it can be concluded that the visual inspection showed an increasing trend for all MCs at the end of the observation period, in particular, MC3 where the failure rate was higher than the other two MCs during the last period.

3.4.3.3 Failure Behaviour of MCs

In Section 3.4.2, the failure analysis methodology was applied to TM3 on MC3, and similarly, the failure behaviour of the rest of the components of MCs1, 2 and 3 were determined and the results reported in Appendix E.

A problem identified was that all components have one or more truncated failure observations (also called suspensions), where the last failure data points of the data set are not failures but merely the end or beginning of the observation period. The addition of these truncated failure observations was done to compensate for the shortcoming in the LTT (as described in section 2.3.3.2.2).

The LTT is performed on the components of the three selected MCs and where the LTT results were in the grey area, the L-R and MK tests were performed. The same methodology is followed for all the MCs, but for simplicity, only the results for MC3 are reported in Table 3.11 and the full results can be seen in Appendix E.

It can be seen from the LTT results, that the compressor, vacuum exhauster and TM4 have reliability degradation trends. By using the LSE method, the data was fitted to either the power law NHPP or the log linear NHPP function. The LTT results were non-committal for the supply sets, traction motor 1 and traction motor 2. For these equipment, the renewable theory HPP was followed, and the failure data was fitted to the Weibull distribution using the linear regression method. The LTT results for TM3 was in the grey area ($U_L=1.73$) and the L-R test was no more conclusive ($U_{LR}=1.59$). Furthermore, with the MK test it was concluded that there was no trend ($S=-7$, $MK=-0.136$) with an 86.4% confidence level, the final conclusion being that the HPP with the Weibull distribution will be the best fit. The Weibull parameters were calculated using the LSE method and adjusted according to a 95% KS goodness-of-fit test, as η=722.15, β=0.764.

Table 3.11: Failure distribution parameters for the main components of MC3

Component	**LTT**	**LTT implication**	**Failure Behaviour**	**Parameters**	
SUPPLY	-0.41	Non-committal	Weibull	η=956.6	β=0.408
COMP	2.71	Reliability Degradation	Log Linear NHPP	α_0=-8.1975	α_0=0.00086
VE	3.03	Reliability Degradation	Log Linear NHPP	α_0=-8.9519	α_0=0.00112
TM1	-0.33	Non-committal	Weibull	η=1441.5	β=0.733
TM2	0.15	Non-committal	Weibull	η=876.5	β=1.046
TM3	1.73	Grey area	After additional tests, HPP concluded.		
			Weibull	η=722.15	β=1.046
TM4	2.20	Reliability Degradation	Log Linear NHPP	α_0=-12.4974	α_0=0.00181

For each component, the KS test was used to determine the goodness-of-fit. The null hypothesis of the KS test states that the data follow the specified distribution, which was rejected when the KS statistic (D_n) was greater than the critical value for the KS test (based on a confidence level of 95%).

3.4.4 Failure Analysis of Train Sets

Once the failure behaviours for all the components were determined, the RBD of a train set could be constructed. Details of the sub-systems are listed in Table 3.9 and the number of components required to survive in a train set is also indicated, where redundancy is evident.

The RBD for a train set, consisting of 3 MCs, is shown in Figure 3.14. It can be seen that more redundancy is present in this configuration compared to a single MC. The supply set, vacuum exhauster and compressed air systems are best described by *k-out-of-n systems*, where two out of three sub-systems are required to be operational for the system to be functional and equation (3) is used to model their behaviour.

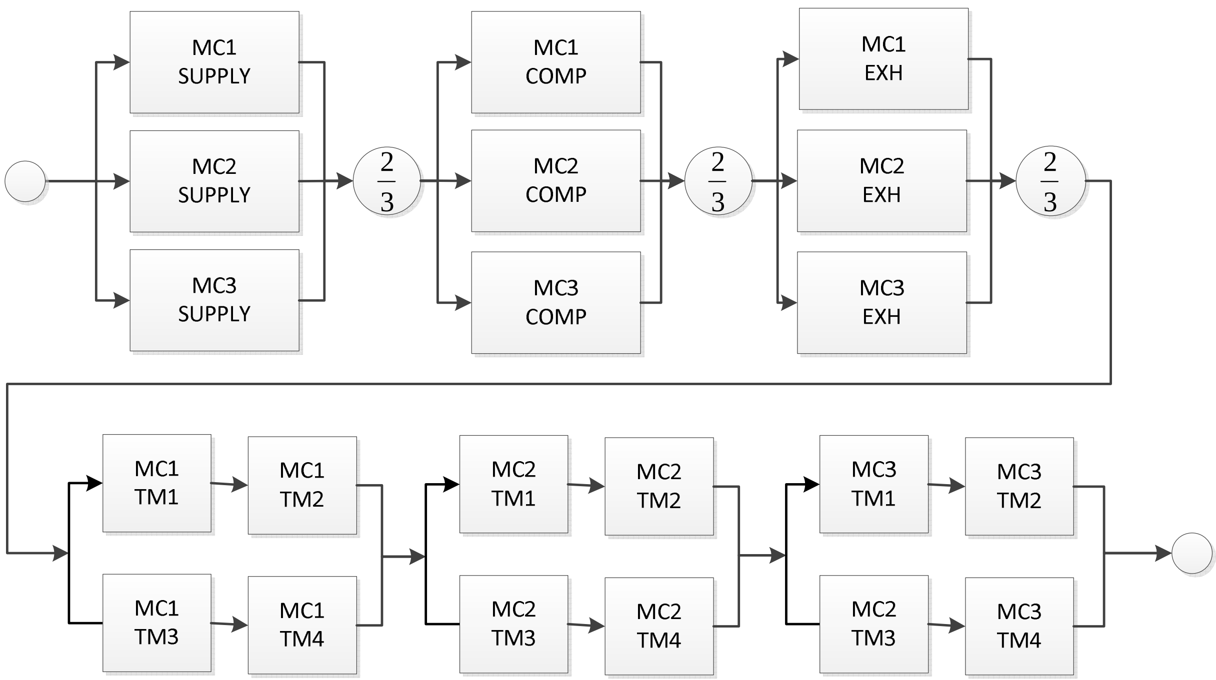


Figure 3.14: Simplified RBD for a 3MC train set

The failure behaviours for the different components for the different MCs were then simulated in the RBD configuration over time, and the results are reported in Chapter 5.

4 DISCUSSION OF RESULTS

In the previous chapters, the literature for reliability was discussed and applied on component level, MC level and train set level. The RBM model was also discussed. In this chapter, the model is used to quantify the reliability of components, MCs and a train set at Metrorail as a case study.

4.1 Discussion of Reliabilities in the Case Study

An analysis was done for the three individual MCs and a train set, made up from these three MCs in the configuration, as shown in the RBD model in Figure 3.14. The reliabilities were calculated using Microsoft® Excel, with the calculated failure behaviours and parameters of components from section 3.4.2.

The reliability of the train set and a comparison of the reliabilities of the MCs are reported in Figure 4.1. It becomes clear that each of the three MCs follows a different reliability trend, where for approximately 200 days, MC2 was the most reliable where after it degrades to less reliable than MC1 and MC3. It can also be seen that there is an initial sharp deterioration in the reliability of MC3, which will be discussed later in this section.

The current maintenance strategy of Metrorail was discussed in section 3.3.2 as well as the differences between the A-Shed, B-Shed and C-Shed maintenance interventions. As discussed, the A-Shed does not add value to the reliability of a MC as it consists of inspection tasks related to safety of the train set, and no maintenance is performed. During the B-Shed and C-Shed maintenance interventions, maintenance is performed on different systems according to the check sheets, but the contribution of the maintenance towards reliability is not quantified.t.

Because of redundancy in the MCs, the reliability of the train set is higher than the reliability of any of the individual MCs (refer to Figure 4.1). From the plot in Figure 4.1, the time period for a reliable life (also called warranty time) can be derived, e.g. the warranty period over 14 days are 92.5% for MC1, 94.7% for MC2 and 83.2% for MC3. The overall warranty period for the train set is 99.1% over 14 days, which is higher than any of the individual reliabilities of the MCs. The implication of the train set reliability is that this train set can only guarantee a reliability of 99.1% over a 14 day period. This equates to almost one train run in every 100 train runs which will be affected by the unreliability of the train set.

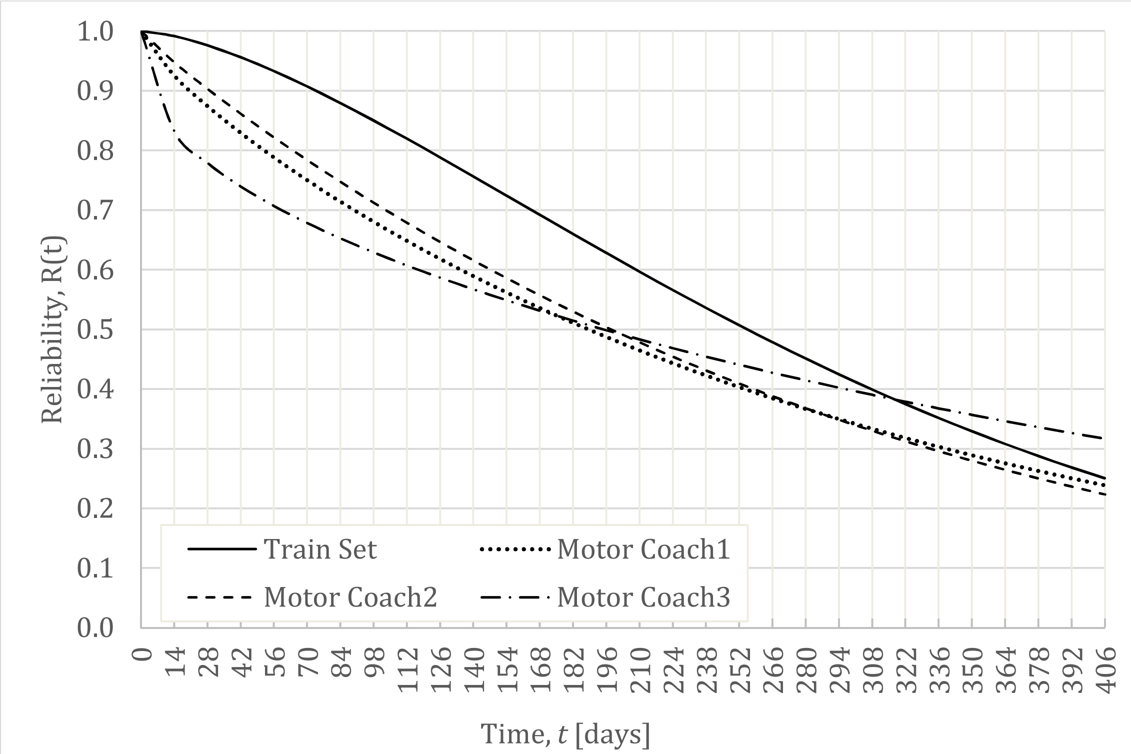


Figure 4.1: Reliability of a train set and the individual reliabilities of MCs

The individual reliability plots for MC1, MC2 and MC3 are shown in Figure 4.2, Figure 4.3 and Figure 4.4. Unlike a train set, the reliability of a MC will be less than the reliability of any sub system, owing to the serial relationship between the components (refer to Figure 3.12). It can be seen in Figure 4.4 that the reliability of MC3 shows an initial sharp decline, and that the supply set contributes to this decline in reliability. Throughout the observation period, the reliability of the supply set is significantly lower than the other sub-systems, thus, negatively impacting the reliability of MC3. It follows that a Weibull distribution with η=956.6 and β=0.408 and the steep reliability degradation can be expected with such a low β-value.

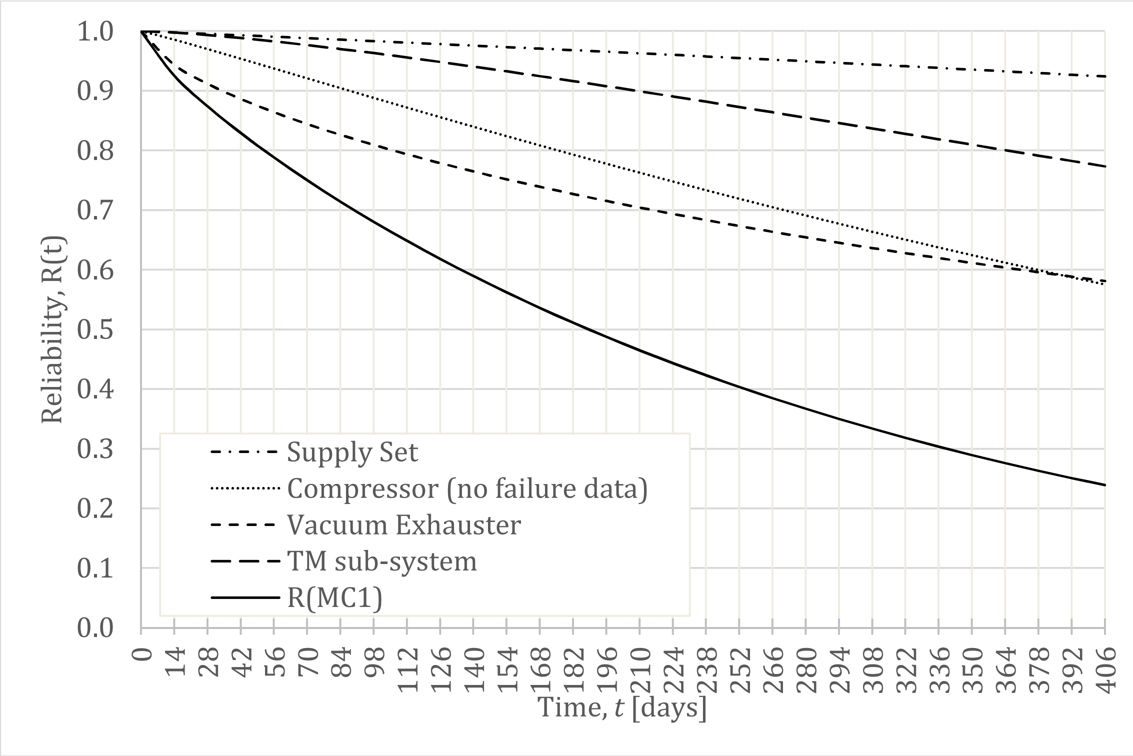


Figure 4.2: Reliability of the individual sub-systems compared to the reliability of MC1

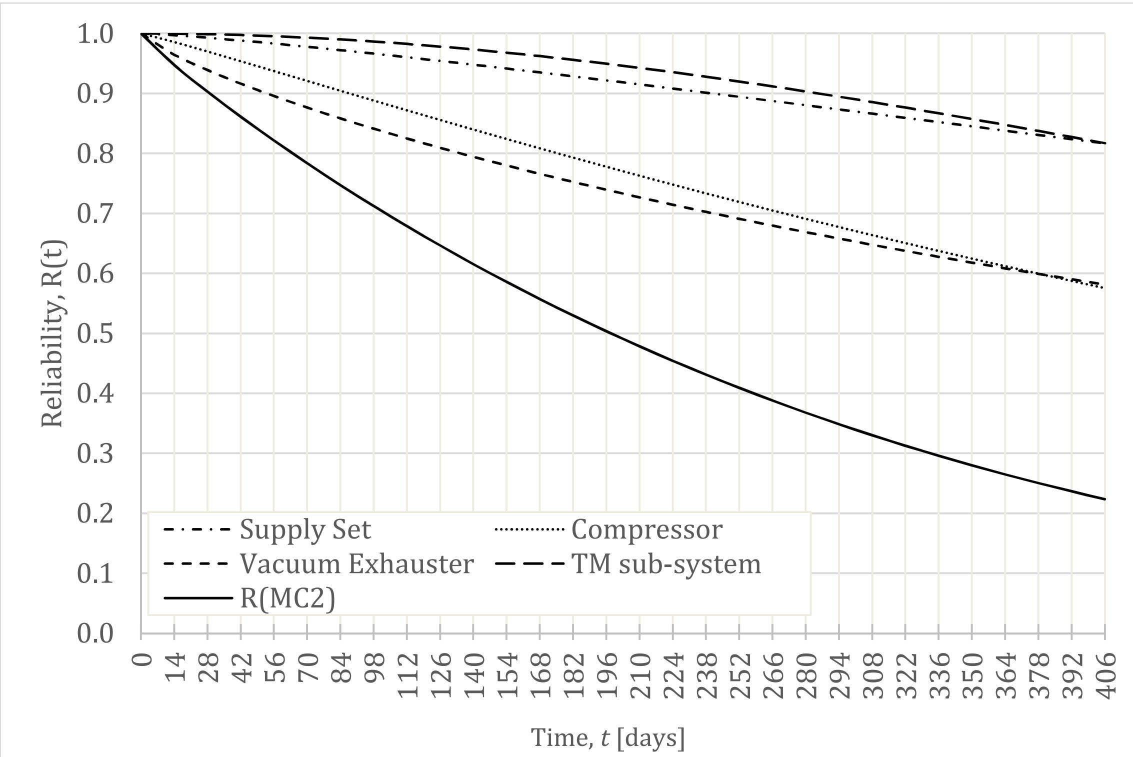


Figure 4.3: Reliability of the individual sub-systems compared to the reliability of MC2

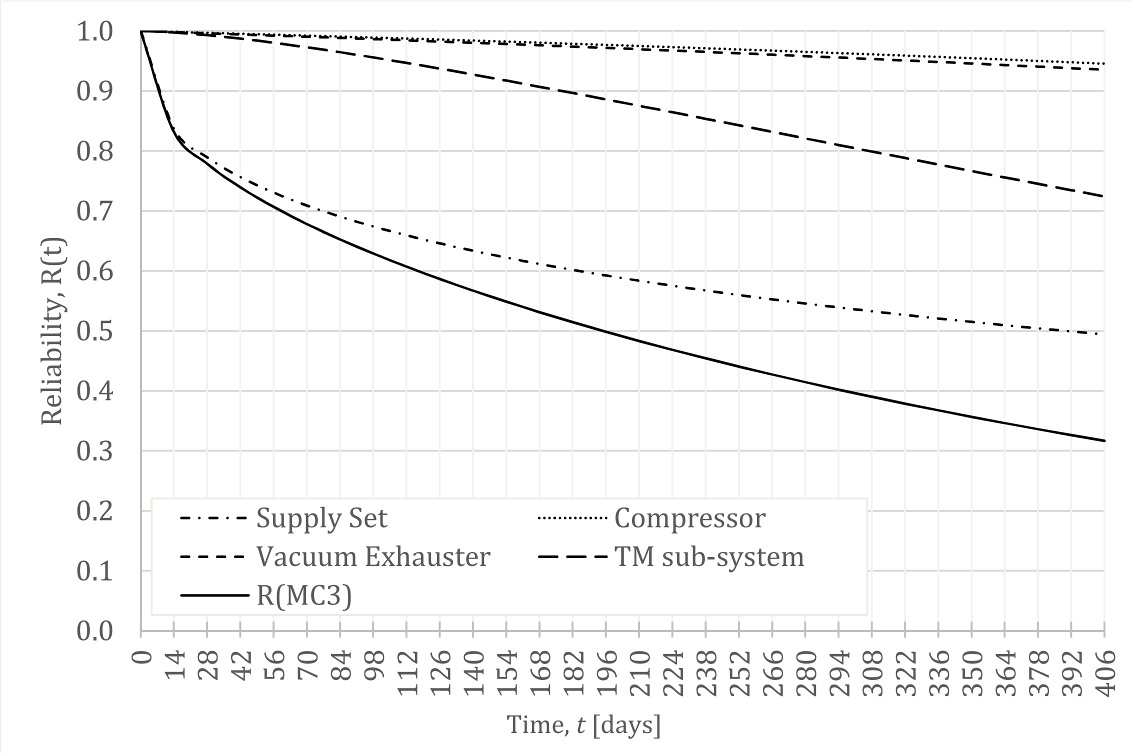


Figure 4.4: Reliability of the individual sub-systems compared to the reliability of MC3

The propulsion system (consisting of four TMs in a sub-system) of MC1 is shown in Figure 4.5. The effect of the series parallel TM configuration can be seen where the reliability of TM3 is degrading faster than the other TMs, but still the reliability of the TM sub-system is relatively high. The reliability of the TM sub-system and the individual TMs after 14 days are listed in Table 4.1.

Table 4.1: Reliability of TM sub-system and individual TMs of MC1 after 14 days

TM1	TM2	TM3	TM4	TM sub-system
97.78%	99.72%	89.83%	99.85%	99.74%

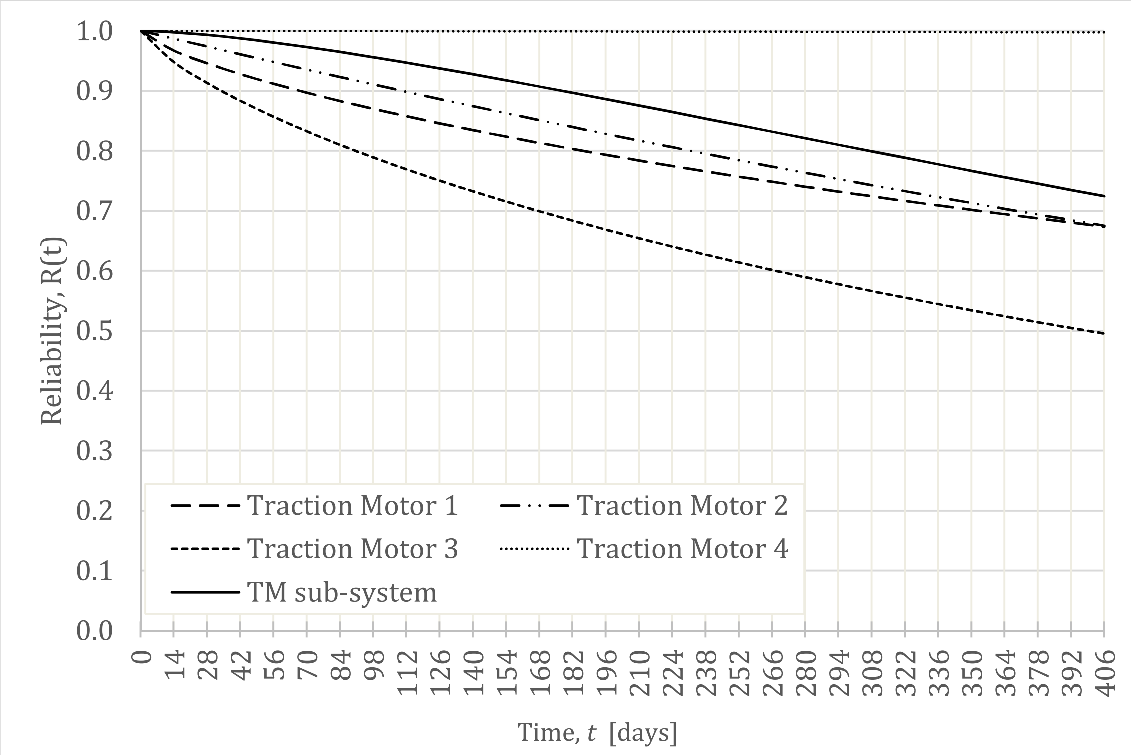


Figure 4.5: Reliability of the propulsion system for MC1

4.2 Prediction of Failures

In the next section, the prediction of failures will be illustrated.

In the first illustration, the prediction of a component failure will be done based on the historic failure behaviour. The original failure observation period was from 18 March 2003 until 12 August 2013, and this failure data was used to model the failure behaviour of the component. During 2014, more failure data was collected from Metrorail, which will be used to validate the failure prediction. Only two components were replaced on the three selected MCs, and it was a simultaneous replacement of two TMs on one bogie (TM1 and TM2 on MC3) on 22 May 2014 (refer to last entries in Table 4.2).

Table 4.2: Replacement history of TMs on MC3

TM1 on MC3		**TM2 on MC3**	
Date	$\boldsymbol{X_i}$	**Date**	$\boldsymbol{X_i}$
18-03-2003	*Note1*	18-03-2003	*Note1*
09-07-2004	479.0	09-07-2004	479.0
23-05-2005	318.7	23-05-2005	318.7
12-08-2013	*Note2* 3002.3	28-09-2006	492.8
22-05-2014	*Note3* 283.0	18-10-2012	2212.0
		22-05-2014	*Note3* 580.5

Note1- start of observation period, truncated failure observation

Note2- end of observation period, truncated failure observation

Note3- additional observation point, replacement of component

Using equation (8), where $\Gamma(n)$ represents the gamma function, the value for n is obtained from the Gamma Table 6.4 in Appendix B and the mean life of TM1 and MC2 are calculated as follows:

Failure prediction for TM1 on MC3:

$$E[T(time-to-failure)] = \eta.\Gamma\left(1+\frac{1}{\beta}\right)$$

$$= 1441.5\,x.\Gamma\left(1+\frac{1}{0.733}\right)$$

$$= 1441.5\,x.\Gamma(2.364)$$

$$= 1441.5\,x0.6261$$

$$= 902.5\,days$$

This can be compared to the actual inter-arrival time of the failure of 283 days, which means that the TM lasted 619.5 days shorter than expected. Various reasons can be given for this, but the most likely reason could be that the truncated failure observation (*Note 2* in Table 4.2) caused a distortion of the failure trend.

Failure prediction for TM2 on MC3:

$$E[T(time-to-failure)] = \eta.\Gamma\left(1+\frac{1}{\beta}\right)$$

$$= 876.5\,x.\Gamma\left(1+\frac{1}{1.046}\right)$$

$$= 876.5\,x.\Gamma(1.956)$$

$$= 876.5\,x0.7172$$

$$= 628.6\,days$$

This can be compared to the actual inter-arrival time of the failure of 580.5 days, which means that the TM only lasted 48.1 days shorter than predicted.

Lastly, the failure prediction of the train set will be done using a single distribution representing the failure behaviour of the complete train set. Using the cumulative failure distribution, *F*(x) can be calculated and a single distribution fitted using the LSE method. The NHPP was chosen and the parameters for the log linear NHPP and power law NHPP distributions calculated, K-S goodness-of-fit test performed. It was concluded that the power law NHPP has the best fit to the failure data. The failure behaviour of the train set can, as illustrated in Figure 4.6 below, be best described by:

$R_2(T_1,T_2) = e^{-\lambda(T_2^\beta - T_1^\beta)}$ where λ= 0.000282 and β=1.355.

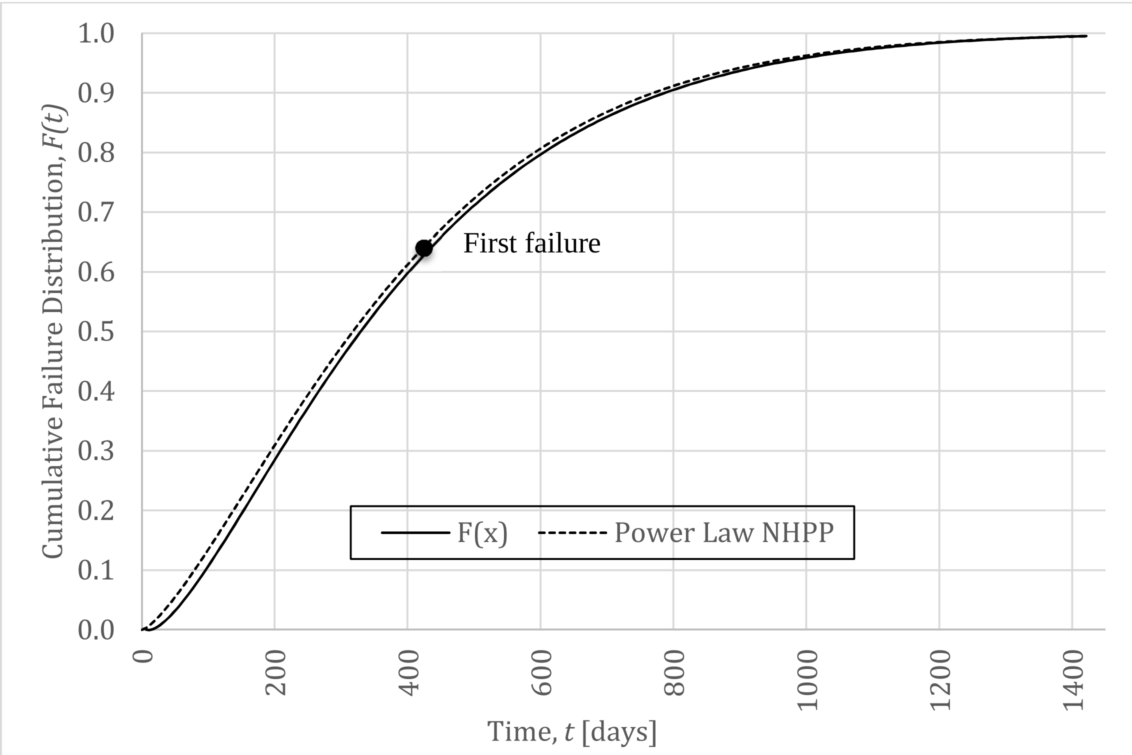


Figure 4.6: Single cumulative failure distribution for the train set, *F(t)*

The expected number of failures, the reliability of the train set and the MTBF can be calculated for different time periods from the power law NHPP formulas in Table 2.4. It can be calculated, for instance, that the first failure of the train set will occur after 415.8 days and the reliability will then be 37%. Other examples are shown in Table 4.3.

Table 4.3: Illustrative failure values for the train set based on a single distribution

Time, T_2 [days]	$E_2(T_2)$	$MTBF(T_2)$	$R(T_2)$
14	0.01	1388.6	98.99%
1000	3.28	30.44	3.74%
415.8	1.00	416.08	36.88%

It can be concluded that failure predictions can be done, and as in the case study, with mixed success. The use of a single distribution representing a train set can be validated against failure data over a longer period.

4.3 Contribution of Maintenance to Reliability

Up to now, the contribution of maintenance was ignored and the reliability graphs for the component, MC or train set was done based only on the historical failures of the components. The contribution of maintenance interventions towards reliability is not quantified, and the contribution to reliability is dependent on the type of maintenance intervention (i.e. A-Shed, B-Shed or C-Shed).

The reliability of a train set and MCs are shown in Figure 4.1. When the periodical maintenance schedules as defined in Table 3.1 are integrated into the timeline, typical reliability graphs can be obtained as shown in Figure 4.7 and Figure 4.8. The maintenance schedule in Table 3.1 is an A-B-A-C schedule based on a two week interval. It can be seen that with maintenance, the reliabilities of the MCs and train set do not tend to zero but tend to be closer to a horizontal line, dependant on the value added by the maintenance interventions.

The contribution of the C-Shed ($R_{C\text{-}Shed}$) towards reliability is most likely twice the contribution of the B-Shed ($R_{B\text{-}Shed}$) towards reliability [72]. Five scenarios as shown in Table 4.4 were tested. The impact of maintenance is illustrated and it can be seen in the table that the overall reliability, 100%, is reached when the contribution of a C-Shed is 4%.

In Figure 4.1, the overall reliability on day 406 is 25% if no maintenance is done. These reliabilities can be compared and an optimum scenario selected. For example, the reliability of scenario 5 is 100% after 406 days, which is not feasible owing to the cost considerations and the consequence of imperfect maintenance.

Table 4.4: Quantify the value adding of maintenance activities

	Scenario 1	Scenario 2	Scenario 3	Scenario4	Scenario 5
A-Shed	0	0	0	0	0
B-Shed	0	0.5%	1.0%	1.5%	2.0%
C-Shed	0	1.0%	2.0%	3.0%	4.0%
$R_{(406)}$	25.0%	55.4%	81.6%	97.0%	100.0%

If the example is followed where the train operations department requires a hypothetical reliability of 98%, the train set reliability with objective function can be optimised by determining the intensity of the maintenance shedding interventions. It can be calculated that:

$R_{406} = f(R_{B-Shed} = 1.55\%, R_{C-Shed} = 3.11\%)) = 0.98$, with $R_{C\text{-}Shed}$=2 x $R_{B\text{-}Shed}$, not taking the mean or standard deviations of the train set reliability over the period into account.

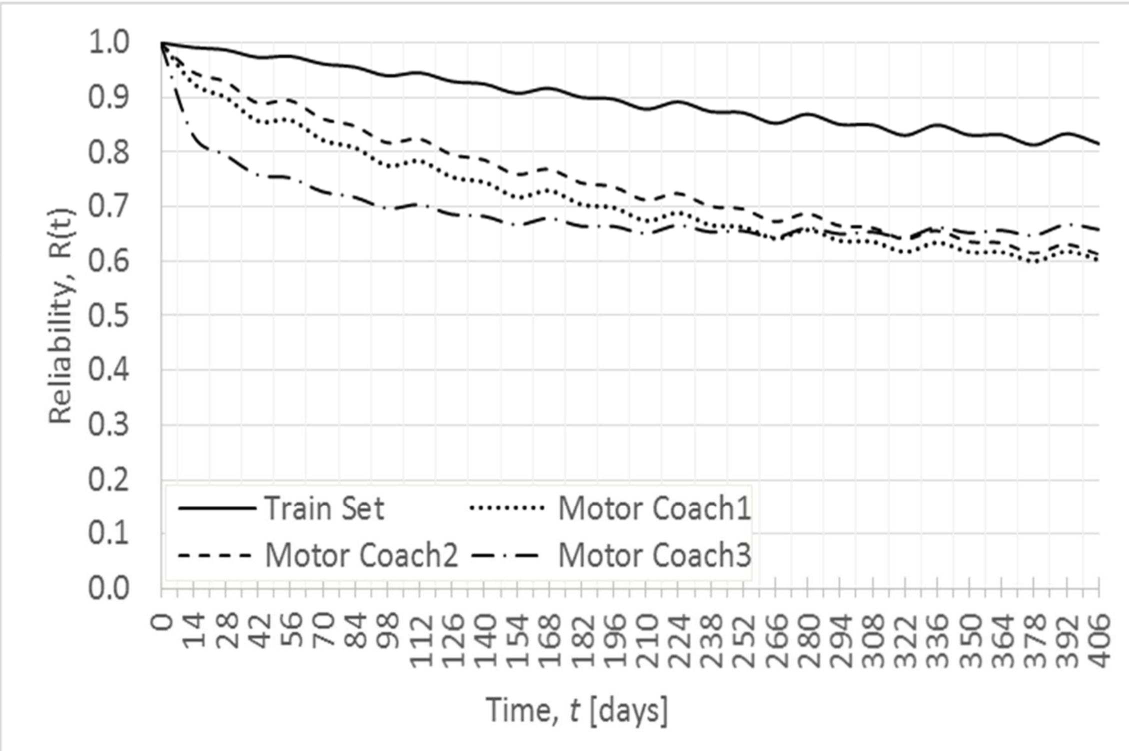


Figure 4.7: Reliability of train set with $R(_{B\text{-}Shed})$=1% and $R(C_{\text{-}Shed})$=2%

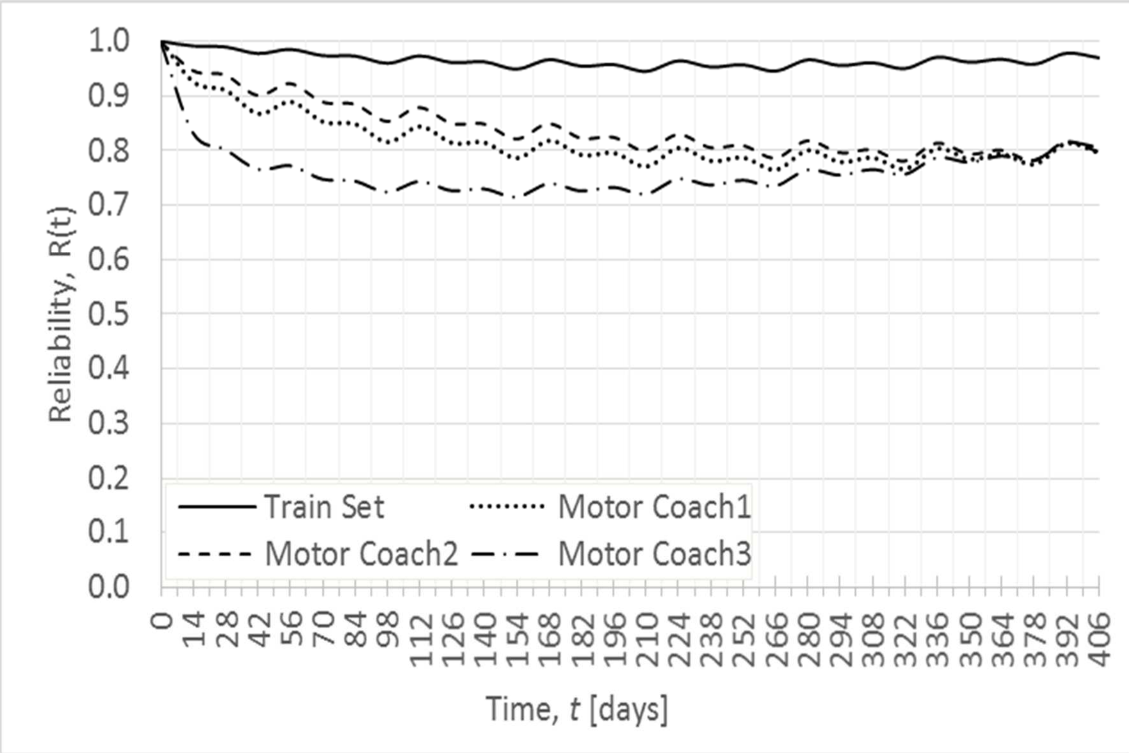


Figure 4.8: Reliability of train set with a $R(_{B\text{-}Shed})$=1.5% and $R(_{C\text{-}Shed})$=3%

4.4 Application of the Reliability Based Maintenance (RBM) Model

The opening statement of the first chapter is that "an effective rail system depends on the seamless integration of a number of complex systems, and if one system fails, the service can be severely affected". Failures of systems contribute to unreliability, and complex systems can include rolling stock, infrastructure, train operation systems and facilities. The relevant departments and role players can make use of the RBM model to manage physical assets. The train operations department can, for example, quantify their expected reliability in terms of the percentage *successful missions* completed, where a successful mission is defined as a train run without failure. Successful missions can be related to the punctuality target, and the relevant departments can then claim an agreed proportion of the allowed unsuccessful missions, then plan the reliability of their assets accordingly.

In section 3.2, the international punctuality benchmark was given as 95% on time, where on-time is defined as arrival at the final destination within 5 minutes. If the train operation department, for example, requires 95% *successful missions*, and it is agreed that the rolling stock maintenance department can claim 2% of the 5% unreliability, then the rolling stock maintenance department must maintain a 98% reliability of the fleet. They can use the RBM model to set up a reliability model, which is described in seven steps and illustrated in Table 4.5:

- Step 1: Calculate the reliabilities of all the MCs in the fleet according to the RBM model.

- Step 2: Sort the reliabilities of the MCs from large to small based on e.g. 14 days.
- Step 3: Categorise the MCs in terms of reliabilities into three groups, e.g.:
  - Group A means very good reliability and requires less maintenance.
  - Group B average reliability.
  - Group C means bad reliability and requires more maintenance.
- Step 4: "Build" train sets from each group, e.g.:
  - Build "good" train sets from the MCs in Group A.
  - Build "average" train sets from the MCs in Group B.
  - Build "bad" train sets from the MCs in Group C.
- Step 5: Based on the agreed unreliability (e.g. 2%), determine the different maintenance intervals and maintenance intensity for the different groups of train sets.
- Step 6: Maintain the groups of train sets according to the RBM Schedule, calculated for each group.
- Step 7: Monitor the reliability of each MC continuously and move the MC to other groups if the reliability increases or decreases.

Table 4.5: Illustrating the application of the RBM concept in maintenance planning

	MC number	Arbitrary Reliability R_{14days}	Train set number	Arbitrary train set reliability R_{14days}	Maintenance Schedule
Group A (R>90%)	MC101	0.90	Train set 1	98.7%	6 weeks
	MC102	0.90			
	MC103	0.92			
	MC104	0.95	Train set 2	99.6%	
	MC105	0.92			
	MC106	0.94			
Group B (80%<R<90%)	MC107	0.85	Train set 3	97.1%	4 weeks
	MC108	0.88			
	MC109	0.81			
	MC110	0.86	Train set 4	97.8%	
	MC111	0.83			
	MC112	0.89			
Group C (R<80%)	MC113	0.78	Train set 5	96.2%	2 weeks
	MC114	0.71			
	MC115	0.74			
	MC116	0.65	Train set 6	95.5%	
	MC117	0.63			
	MC118	0.57			

In this study, the reliabilities of only three MCs were calculated and the same can be done for all the MCs in the fleet. The concept of RBM is illustrated in Table 4.5, where the reliabilities of 18 MCs are ranked and six train sets are made up from these MCs. Train set 1 and 2 are classified as “good” train sets (group A), which will require less frequent maintenance interventions, i.e. every six weeks. Train set 3 and 4 from group B are classified as “average” train sets and will require more frequent maintenance than Group A, i.e. every four weeks. Lastly train set 5 and 6 are classified as “bad” train sets requiring frequent maintenance, i.e. every 2 weeks.

The reliability of the train fleet must be agreed upon by the train operations department and the rolling stock maintenance department. It is indicated in Figure 4.9 that the guaranteed reliability of the original train set (consisting of the original MC1, MC2 and MC3) over a 14 day period will be 99.2%, reaching 97.8% after 28 days.

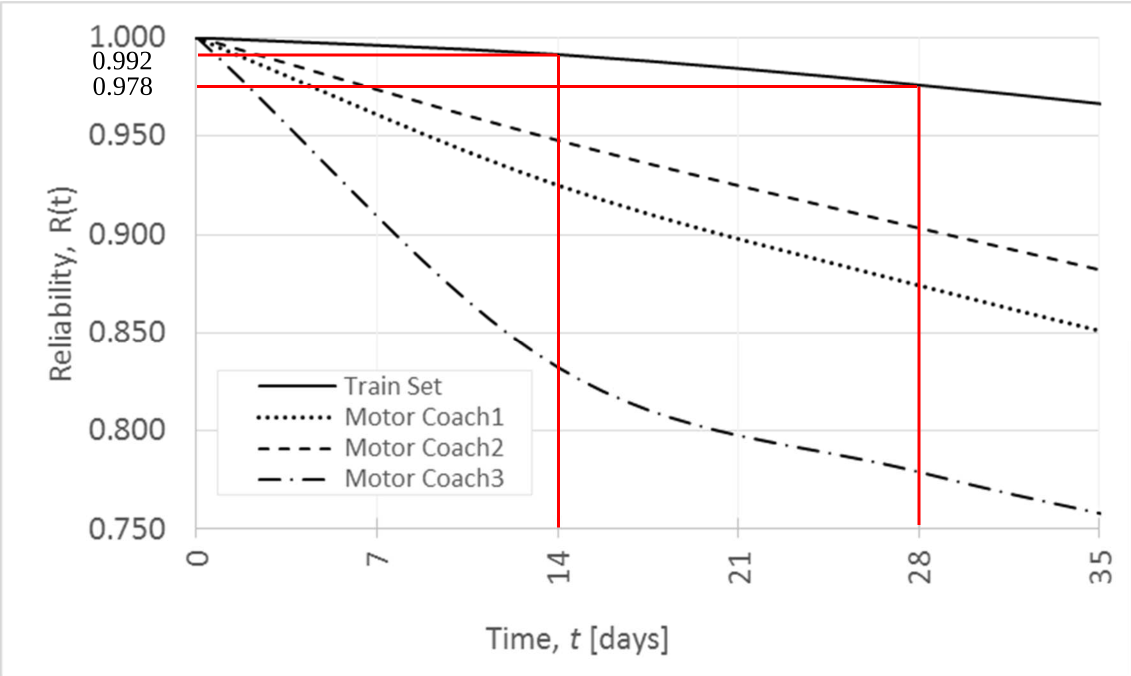


Figure 4.9: Reliability during a 35-day window for train set and the individual MCs

5 CONCLUSION

The management of engineering assets becomes more critical in asset intensive organisations. In this study, the reliability of a rail transportation system was quantified for an aging fleet. The objective of the study was to develop a scientific approach to quantify the reliability of the rolling stock fleet in order to develop a maintenance planning model based on system reliability. Although various reliability methods and techniques are available for the reliability engineer, a Reliability Based Maintenance (RBM) model was selected as it is effective in modular engineering asset applications. This model uses failure statistics of components, sub-systems and systems.

The research methodology followed made use of failure statistics, failure distributions and the interdependence of different systems to determine the impact of component failures on the overall system reliability. The individual reliabilities of MCs could be determined and specific train sets built according to reliability ratings. The selection of components took into account factors such as risks, likelihood of failure and consequence of failure. Trend analysis techniques were extensively used to assist with the selection of the most appropriate failure distribution. Similarly, parameter estimation techniques were used to determine parameters while goodness-of-fit tests were used to ensure parameter integrity. Seeing that train sets consist of PTs and MCs, the contribution of PTs to the reliability of train sets could not be ignored. Thus, the failures of the MCs are modelled representing the train sets. The RBD model that was constructed for the MC and the train sets made use of redundancy in the system. Various reliability scenarios were also simulated using Microsoft® Excel.

This model, which was validated with real data, helped to illustrate how the reliability measure can be used to determine maintenance intervals of different train sets. Based on the results, recommendations are made in relation to future planning of the maintenance strategy. The value proposition of the RBM model was demonstrated in a maintenance planning application. It was shown how reliability values of all MCs can be ranked into various groups after which train sets can be built from “reliable” MCs, working down the order of reliability values, finishing with train sets build from “less reliable” MCs. It was also shown how maintenance intervals can be suggested to suit the different groups of train sets and how the value-added by the maintenance function, can be managed by optimising both the reliability intensity of the ABC-Sheds as well as the time between maintenance intervals. The RBM model could also predict component and train set failures. The model illustrated ways how an agreed reliability of hypothetical 98% can be achieved by ensuring that the contribution of planned maintenance interventions is effective and supports the reliability targets.

With regard to the objectives of this study, it can be concluded that a scientific model was developed to quantify the reliability of the rolling stock fleet, in lieu of cancelations and delays and; that a maintenance planning model was developed for railway rolling stock based on system reliability. The RBM model developed can also complement current maintenance techniques such as CBM, in focussing the maintenance effort where it is required most. In so doing, the reliability of the train sets can be increased, ultimately providing a reliable and punctual service to the commuter.

Future work

In the course of this study, other areas were identified that may be worth investigating in the future:

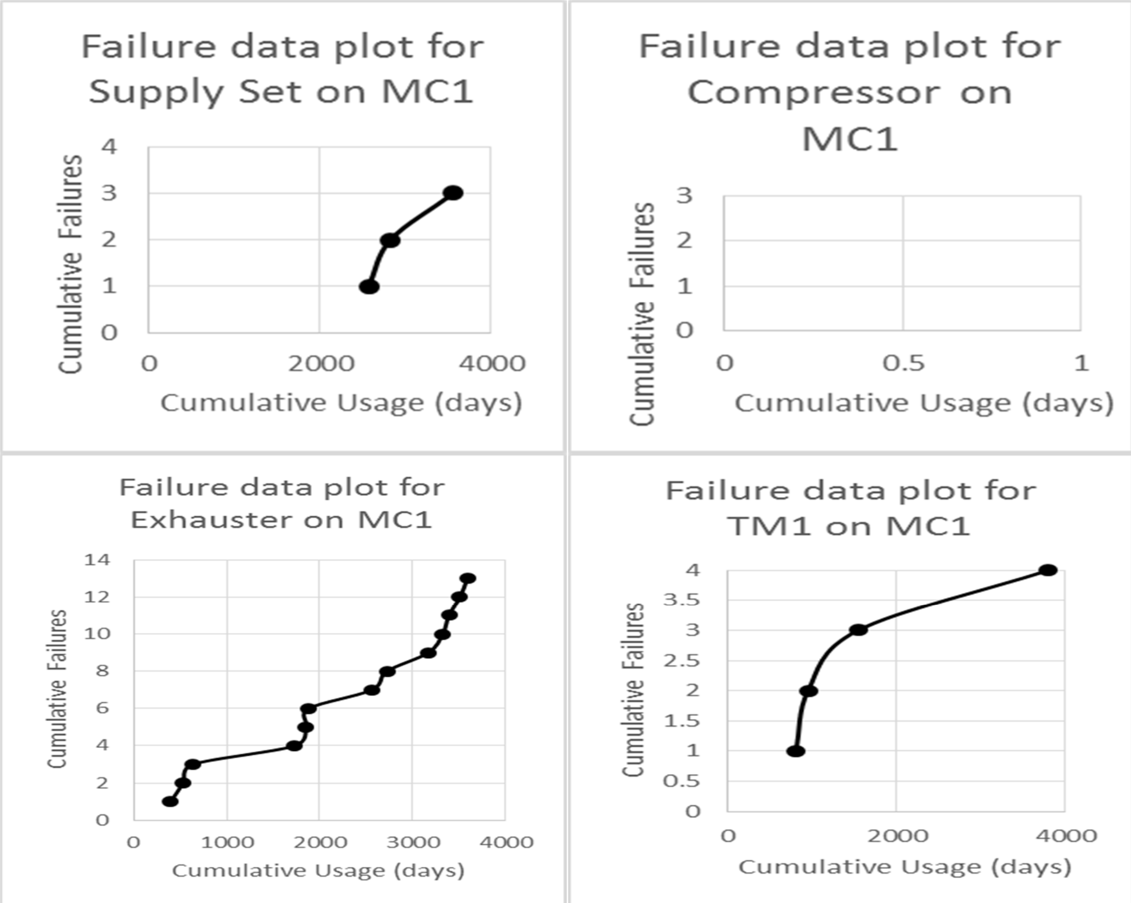
- The RBD could be expanded to contain more components while balancing the contribution of each system.
- Additionally, future models should accommodate components with low or no number of failures in the observation period, by using techniques like the Bayesian approach.
- Metrology could also be used as real time CBM inputs into the model whereby the “theoretical” age of the component will be compared to the environment and other measurements and flagged when inconsistencies are detected. Although the model in this study was done in Microsoft® Excel, a live model can add more value as it would calculate the failure behaviour after each failure.
- Finally, the contribution of maintenance can be studied and each maintenance activity quantified in order to understand the contribution of maintenance to overall system reliability.

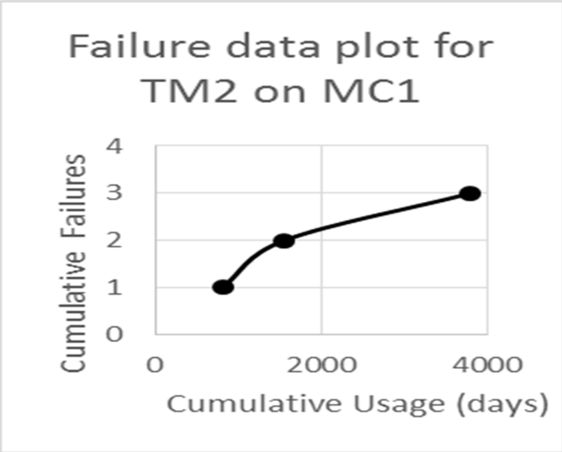
6 Appendices

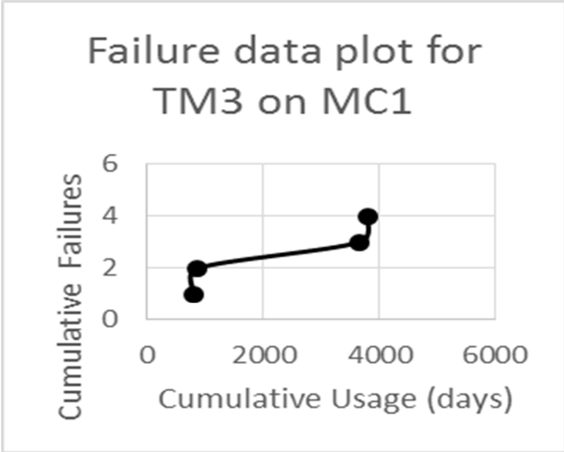
Appendix A : ROCOF Graphs for All Components

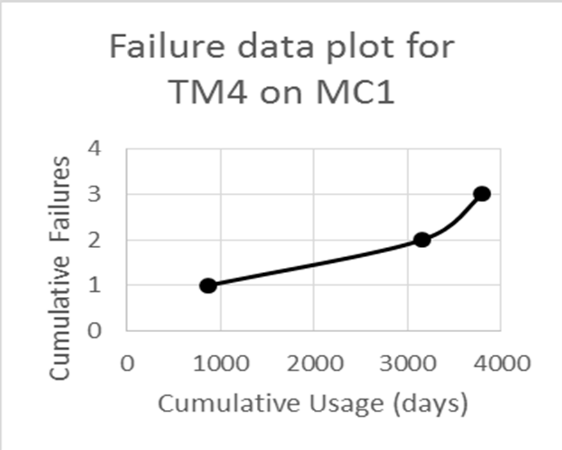
Appendix A summarises the failure behaviours of the different components found on the Metrorail train sets. Failure behaviours are represented by graphs showing the Rate of Occurrence of Failures (ROCOF) and the components for each MC is grouped separately.

ROCOF graphs for components on MC1

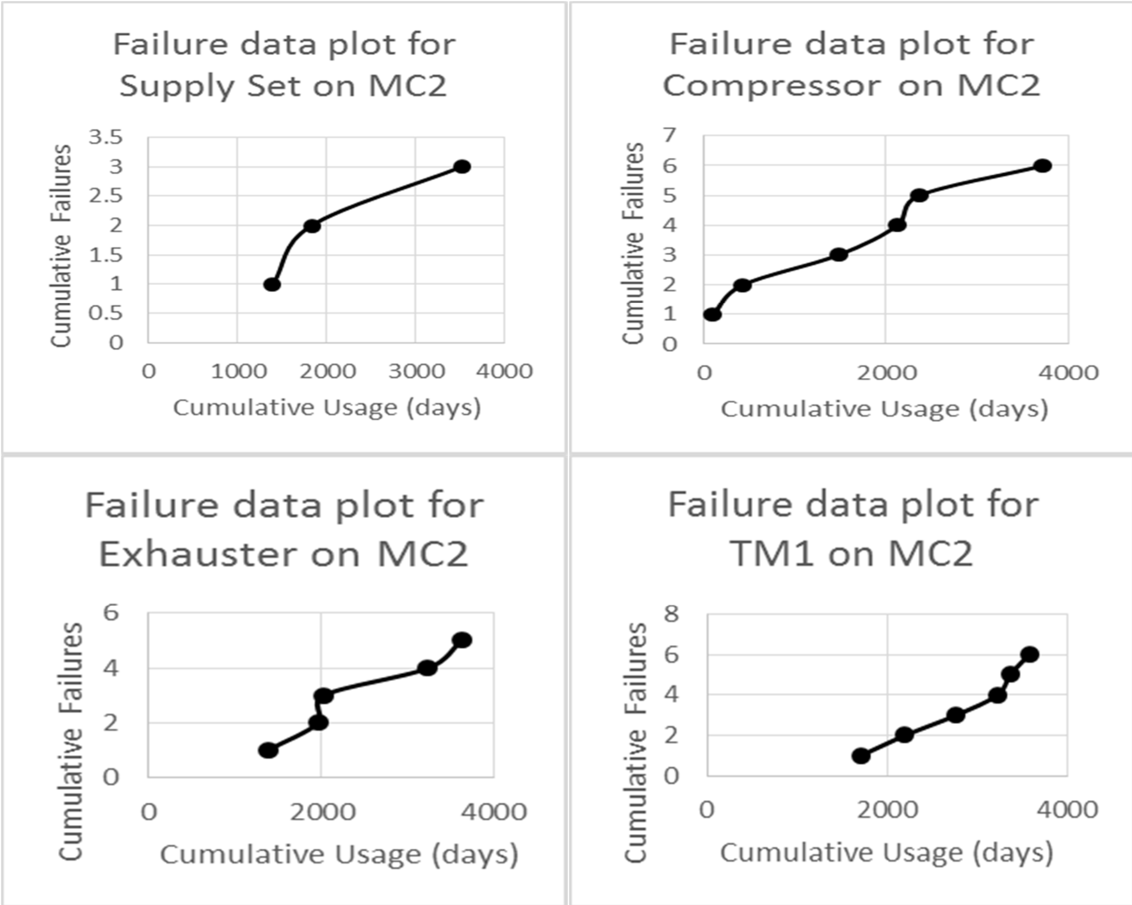


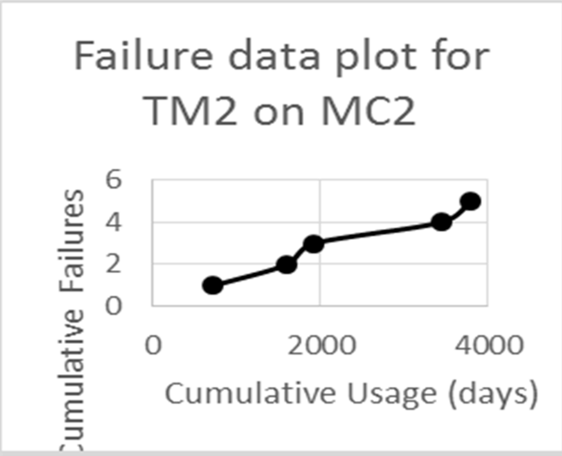

Failure data plot for TM2 on MC1
Cumulative Failures
0
1
2
3
4
0
2000
4000
Cumulative Usage (days)

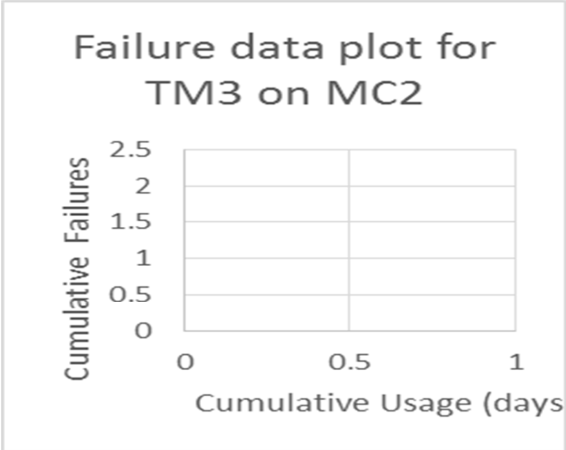

Failure data plot for TM3 on MC1
Cumulative Failures
0
2
4
6
0
2000
4000
6000
Cumulative Usage (days)

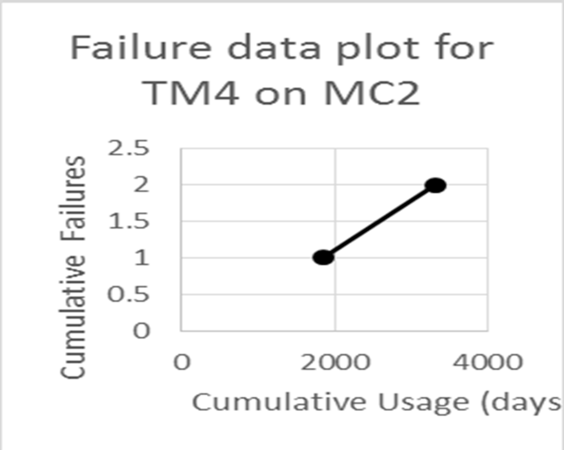

Failure data plot for TM4 on MC1
Cumulative Failures
0
1
2
3
4
0
1000
2000
3000
4000
Cumulative Usage (days)

ROCOF graphs for components on MC2

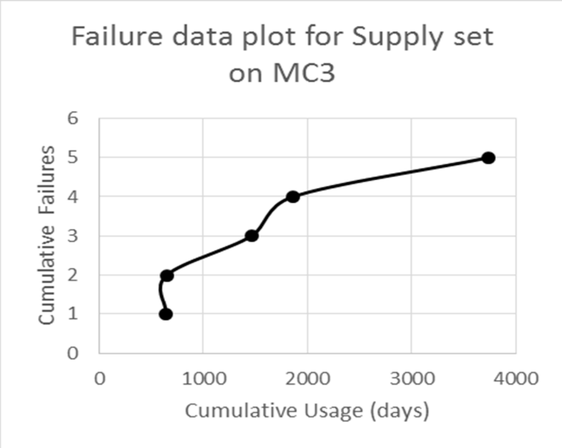


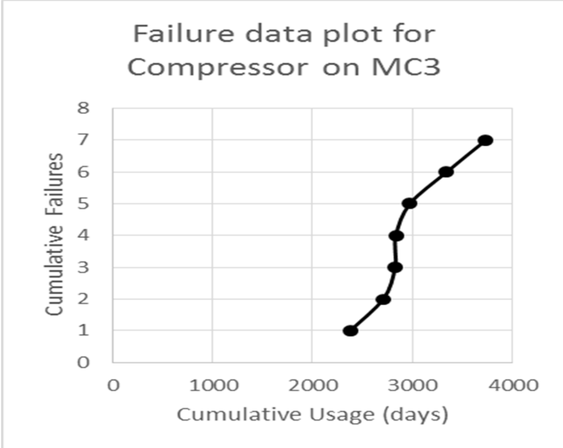

Failure data plot for TM2 on MC2
Cumulative Failures
6
4
2
0
0
2000
4000
Cumulative Usage (days)

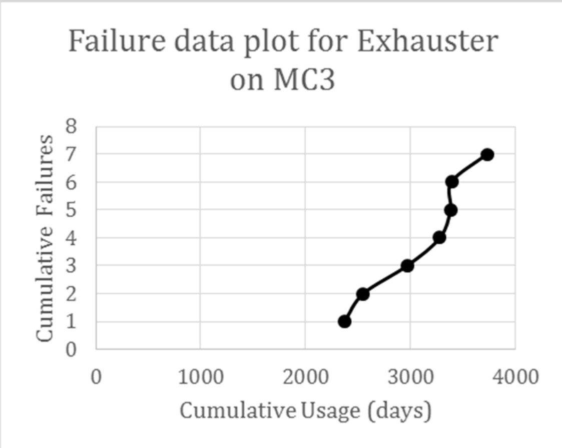

Failure data plot for TM3 on MC2
Cumulative Failures
2.5
2
1.5
1
0.5
0
0
0.5
1
Cumulative Usage (days

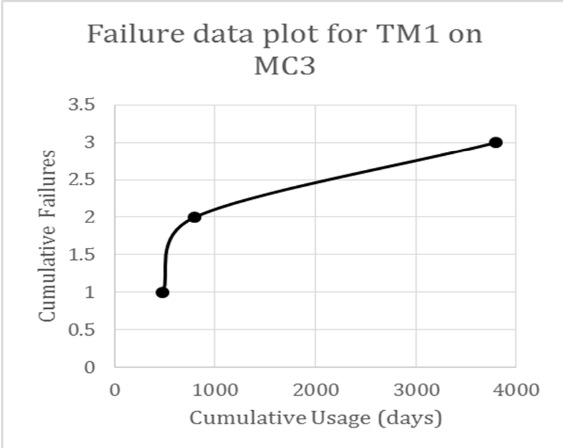

Failure data plot for TM4 on MC2
Cumulative Failures
2.5
2
1.5
1
0.5
0
0
2000
4000
Cumulative Usage (days

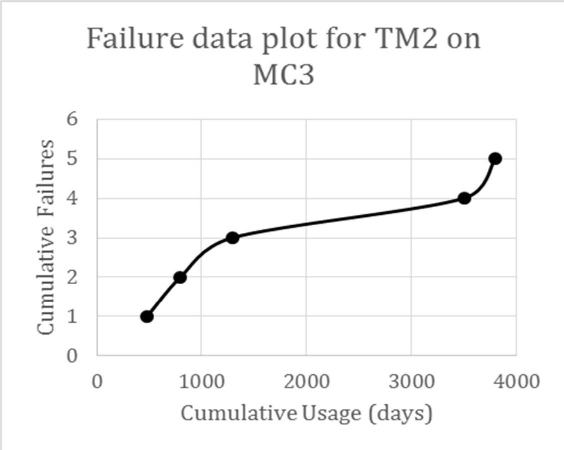
ROCOF graphs for components on MC3

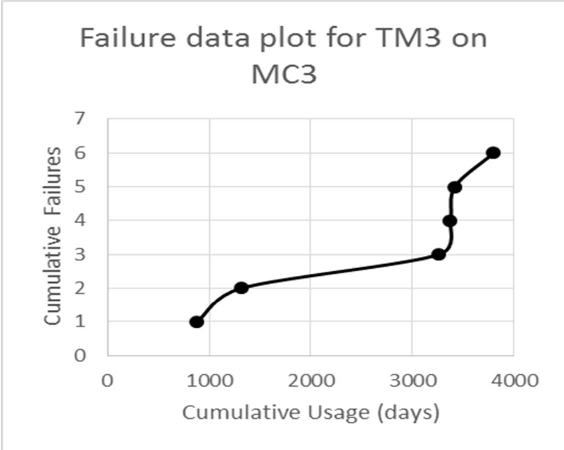


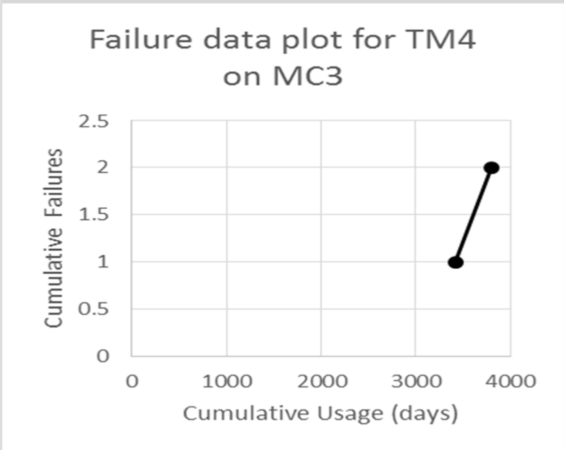







Failure data plot for TM2 on MC3
Cumulative Failures
0
1
2
3
4
5
6
0
1000
2000
3000
4000
Cumulative Usage (days)


Failure data plot for TM3 on MC3
Cumulative Failures
0
1
2
3
4
5
6
7
0
1000
2000
3000
4000
Cumulative Usage (days)


Failure data plot for TM4 on MC3
Cumulative Failures
0
0.5
1
1.5
2
2.5
0
1000
2000
3000
4000
Cumulative Usage (days)

Appendix B: Statistical Tables

In the literature review, references are made to statistical tables used by the Laplace Trend Test, Mann-Kendall trend test, Kolmogorov-Smirnov goodness-of-fit test and the Gamma table from the gamma function. The tables are referenced from various sources.

Table 6.1: Values of z_α corresponding to α for the Cumulative Normal Distribution [52]

z	.00	.01	.02	.03	.04	.05	.06	.07	.08	.09
.0	.5000	.5040	.5080	.5120	.5160	.5199	.5239	.5279	.5319	.5359
.1	.5398	.5438	.5478	.5517	.5557	.5596	.5636	.5675	.5714	.5753
.2	.5793	.5832	.5871	.5910	.5948	.5987	.6026	.6064	.6103	.6141
.3	.6179	.6217	.6255	.6293	.6331	.6368	.6406	.6443	.6480	.6517
.4	.6554	.6591	.6628	.6664	.6700	.6736	.6772	.6808	.6844	.6879
.5	.6915	.6950	.6985	.7019	.7054	.7088	.7123	.7157	.7190	.7224
.6	.7257	.7291	.7324	.7357	.7389	.7422	.7454	.7486	.7517	.7549
.7	.7580	.7611	.7642	.7673	.7704	.7734	.7764	.7794	.7823	.7852
.8	.7881	.7910	.7939	.7967	.7995	.8023	.8051	.8078	.8106	.8133
.9	.8159	.8186	.8212	.8238	.8264	.8289	.8315	.8340	.8365	.8389
1.0	.8413	.8438	.8461	.8485	.8508	.8531	.8554	.8577	.8599	.8621
1.1	.8643	.8665	.8686	.8708	.8729	.8749	.8770	.8790	.8810	.8830
1.2	.8849	.8869	.8888	.8907	.8925	.8944	.8962	.8980	.8997	.9015
1.3	.9032	.9049	.9066	.9082	.9099	.9115	.9131	.9147	.9162	.9177
1.4	.9192	.9207	.9222	.9236	.9251	.9265	.9279	.9292	.9306	.9319
1.5	.9332	.9345	.9357	.9370	.9382	.9394	.9406	.9418	.9429	.9441
1.6	.9452	.9463	.9474	.9484	.9495	.9505	.9515	.9525	.9535	.9545
1.7	.9554	.9564	.9573	.9582	.9591	.9599	.9608	.9616	.9625	.9633
1.8	.9641	.9649	.9656	.9664	.9671	.9678	.9686	.9693	.9699	.9706
1.9	.9713	.9719	.9726	.9732	.9738	.9744	.9750	.9756	.9761	.9767
2.0	.9772	.9778	.9783	.9788	.9793	.9798	.9803	.9808	.9812	.9817
2.1	.9821	.9826	.9830	.9834	.9838	.9842	.9846	.9850	.9854	.9857
2.2	.9861	.9864	.9868	.9871	.9875	.9878	.9881	.9884	.9887	.9890
2.3	.9893	.9896	.9898	.9901	.9904	.9906	.9909	.9911	.9913	.9916
2.4	.9918	.9920	.9922	.9925	.9927	.9929	.9931	.9932	.9934	.9936
2.5	.9938	.9940	.9941	.9943	.9945	.9946	.9948	.9949	.9951	.9952
2.6	.9953	.9955	.9956	.9957	.9959	.9960	.9961	.9962	.9963	.9964
2.7	.9965	.9966	.9967	.9968	.9969	.9970	.9971	.9972	.9973	.9974
2.8	.9974	.9975	.9976	.9977	.9977	.9978	.9979	.9979	.9980	.9981
2.9	.9981	.9982	.9982	.9983	.9984	.9984	.9985	.9985	.9986	.9986
3.0	.9987	.9987	.9987	.9988	.9988	.9989	.9989	.9989	.9990	.9990
3.1	.9990	.9991	.9991	.9991	.9992	.9992	.9992	.9992	.9993	.9993
3.2	.9993	.9993	.9994	.9994	.9994	.9994	.9994	.9995	.9995	.9995
3.3	.9995	.9995	.9995	.9996	.9996	.9996	.9996	.9996	.9996	.9997
3.4	.9997	.9997	.9997	.9997	.9997	.9997	.9997	.9997	.9997	.9998

Table 6.2: Probabilities for the Mann-Kendall Nonparametric test for trend [52]

	Values of n					Values of n		
S	4	5	8	9	S	6	7	10
0	0.625	0.592	0.548	0.540	1	0.500	0.500	0.500
2	0.375	0.408	0.452	0.460	3	0.360	0.386	0.431
4	0.167	0.242	0.360	0.381	5	0.235	0.281	0.364
6	0.042	0.117	0.274	0.306	7	0.136	0.191	0.300
8		0.042	0.199	0.238	9	0.068	0.119	0.242
10		$0.0^{2}83$	0.138	0.179	11	0.028	0.068	0.190
12			0.089	0.130	13	$0.0^{2}83$	0.035	0.146
14			0.054	0.090	15	$0.0^{2}14$	0.015	0.108
16			0.031	0.060	17		$0.0^{2}54$	0.078
18			0.016	0.038	19		$0.0^{2}14$	0.054
20			$0.0^{2}71$	0.022	21		$0.0^{3}20$	0.036
22			$0.0^{2}28$	0.012	23			0.023
24			$0.0^{3}87$	$0.0^{2}63$	25			0.014
26			$0.0^{3}19$	$0.0^{2}29$	27			$0.0^{2}83$
28			$0.0^{4}25$	$0.0^{2}12$	29			$0.0^{2}46$
30				$0.0^{3}43$	31			$0.0^{2}23$
32				$0.0^{3}12$	33			$0.0^{2}11$
34				$0.0^{4}25$	35			$0.0^{3}47$
36				$0.0^{5}28$	37			$0.0^{3}18$
					39			$0.0^{4}58$
					41			$0.0^{4}15$
					43			$0.0^{5}28$
					45			$0.0^{6}28$

Source: From Kendall, 1975. Used by permission.
Repeated zeros are indicated by powers; for example, $0.0^{3}47$ stands for 0.00047.
Each table entry is the probability that the Mann-Kendall statistic S equals or exceeds the specified value of S when no trend is present.
This table is used in Section 16.4.1.

Table 6.3: Kolmogorov-Smirnov critical *d*-value [73]

n \ α	0.01	0.05	0.1	0.15	0.2
1	0.995	0.975	0.950	0.925	0.900
2	0.929	0.842	0.776	0.726	0.684
3	0.828	0.708	0.642	0.597	0.565
4	0.733	0.624	0.564	0.525	0.494
5	0.669	0.565	0.510	0.474	0.446
6	0.618	0.521	0.470	0.436	0.410
7	0.577	0.486	0.438	0.405	0.381
8	0.543	0.457	0.411	0.381	0.358
9	0.514	0.432	0.388	0.360	0.339
10	0.490	0.410	0.368	0.342	0.322
11	0.468	0.391	0.352	0.326	0.307
12	0.450	0.375	0.338	0.313	0.295
13	0.433	0.361	0.325	0.302	0.284
14	0.418	0.349	0.314	0.292	0.274
15	0.404	0.338	0.304	0.283	0.266
16	0.392	0.328	0.295	0.274	0.258
17	0.381	0.318	0.286	0.266	0.250
18	0.371	0.309	0.278	0.259	0.244
19	0.363	0.301	0.272	0.252	0.237
20	0.356	0.294	0.264	0.246	0.231
25	0.320	0.270	0.240	0.220	0.210
30	0.290	0.240	0.220	0.200	0.190
35	0.270	0.230	0.210	0.190	0.180
40	0.250	0.210	0.190	0.180	0.170
45	0.240	0.200	0.180	0.170	0.160
50	0.230	0.190	0.170	0.160	0.150
OVER 50	$\frac{1.63}{\sqrt{n}}$	$\frac{1.36}{\sqrt{n}}$	$\frac{1.22}{\sqrt{n}}$	$\frac{1.14}{\sqrt{n}}$	$\frac{1.07}{\sqrt{n}}$

Table 6.4: Gamma Table for the Gamma function [19]

n	$\Gamma(n)$	n	$\Gamma(n)$	n	$\Gamma(n)$	n	$\Gamma(n)$
0.0100	99.4327	0.2600	3.4785	0.5100	1.7384	0.7600	1.2123
0.0200	49.4423	0.2700	3.3426	0.5200	1.7058	0.7700	1.1997
0.0300	32.7850	0.2800	3.2169	0.5300	1.6747	0.7800	1.1875
0.0400	24.4610	0.2900	3.1001	0.5400	1.6448	0.7900	1.1757
0.0500	19.4701	0.3000	2.9916	0.5500	1.6161	0.8000	1.1642
0.0600	16.1457	0.3100	2.8903	0.5600	1.5886	0.8100	1.1532
0.0700	13.7736	0.3200	2.7958	0.5700	1.5623	0.8200	1.1425
0.0800	11.9966	0.3300	2.7072	0.5800	1.5369	0.8300	1.1322
0.0900	10.6162	0.3400	2.6242	0.5900	1.5126	0.8400	1.1222
0.1000	9.5135	0.3500	2.5461	0.6000	1.4892	0.8500	1.1125
0.1100	8.6127	0.3600	2.4727	0.6100	1.4667	0.8600	1.1031
0.1200	7.8632	0.3700	2.4036	0.6200	1.4450	0.8700	1.0941
0.1300	7.2302	0.3800	2.3383	0.6300	1.4242	0.8800	1.0853
0.1400	6.6887	0.3900	2.2765	0.6400	1.4041	0.8900	1.0768
0.1500	6.2203	0.4000	2.2182	0.6500	1.3848	0.9000	1.0686
0.1600	5.8113	0.4100	2.1628	0.6600	1.3662	0.9100	1.0607
0.1700	5.4512	0.4200	2.1104	0.6700	1.3482	0.9200	1.0530
0.1800	5.1318	0.4300	2.0605	0.6800	1.3309	0.9300	1.0456
0.1900	4.8468	0.4400	2.0132	0.6900	1.3142	0.9400	1.0384
0.2000	4.5908	0.4500	1.9681	0.7000	1.2981	0.9500	1.0315
0.2100	4.3599	0.4600	1.9252	0.7100	1.2825	0.9600	1.0247
0.2200	4.1505	0.4700	1.8843	0.7200	1.2675	0.9700	1.0182
0.2300	3.9598	0.4800	1.8453	0.7300	1.2530	0.9800	1.0119
0.2400	3.7855	0.4900	1.8080	0.7400	1.2390	0.9900	1.0059
0.2500	3.6256	0.5000	1.7725	0.7500	1.2254	1.0000	1.0000

Appendix C: Detail Regression Output Results for TM3 on MC3

Parameter estimation for the two parameter Weibull distribution can be done with linear regression. This appendix shows the regression output results from Microsoft® Excel used to calculate the parameters for the TMs for MC3.

Table 6.5: Detailed regression output results for TM3 on MC3

Linear Regression is used to calculate the parameters β and η for the two parameter Weibull distribution.

LINEAR REGRESSION SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.99046
R Square	0.98101
Adjusted R Square	0.97627
Standard Error	0.16331
Observations	6

ANOVA

	df	SS	MS	F	Significance F
Regression	1	5.51179	5.51179	206.66743	0.00014
Residual	4	0.10668	0.02667		
Total	5	5.61847			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	-4.94294	0.31612	-15.63607	0.00010	-5.82064	-4.06524	-5.82064	-4.06524
X Variable 1	0.76422	0.05316	14.37593	0.00014	0.61663	0.91182	0.61663	0.91182

$$\beta = \text{"X Variable 1"} = 0.764$$

$$\eta = e^{-(\frac{c}{\beta})} = e^{-(\frac{\text{"Intercept"}}{\beta})} = e^{-(\frac{-4.943}{0.764})} = 644.141$$

RESIDUAL OUTPUT

Observation	Predicted Y	Residuals
1	-2.05097	-0.10465
2	-1.33695	0.16168
3	-0.39830	-0.20324
4	-0.30206	0.15478
5	0.23989	0.04203
6	0.84494	-0.05060

Appendix D: Typical Data Set from FMMS

Maintenance data is entered in a Facility Maintenance Management System currently used by Metrorail. The data is accessed by building a query extracting the data from the SQL database. Surprisingly, the data is well indexed and there is too much data available. This appendix shows a part of the data extracted from the database.

Table 6.6: Typical raw data set from FMMS

Job Title	Facility Code	Fmmsctn Job Reference.Description	Serial Number	Date Act End
EXHAUSTER, R&R	10M30016M_UNDER_EXH	Oil Level Low	EXHS#914501/39	28-11-2002 10:00
TRACTION MOTOR, R&R	13120_BOG2_TM3	Armature Defective	TMOS#262804	18-03-2003 00:00
TRACTION MOTOR, R&R	13120_BOG2_TM3	Armature Defective/ Earthed	TMOS#262804	18-03-2003 00:00
TRACTION MOTOR, R&R	10M51515M_BOG1_TM1	Armature Defective/ Earthed	TMCB#313971	12-05-2003 00:00
TRACTION MOTOR, R&R	10M51515M_BOG1_TM1	Armature Defective	TMCB#313971	12-05-2003 00:00
MA/MG, R&R	13543_UNDER_AUX_SUPPLY	Test / Examination		17-05-2003 00:00
COMPRESSOR, R&R	17667_UNDER_COMP	Weak	CMPR#35857	21-05-2003 00:00
TRACTION MOTOR, R&R	13159_BOG2_TM3	Ext. Cables /Connections / Boxes Def	TMCB#289574	28-05-2003 00:00
TRACTION MOTOR, R&R	13138_BOG1_TM1	Low Megger Reading	TMOS#261920	30-05-2003 00:00
MA/MG, R&R	13186_UNDER_AUX_SUPPLY	Brushes Worn / Chipped / Sticky	MALT#LB453P	30-05-2003 00:00
EXHAUSTER, R&R	13139_UNDER_EXH	Weak	EXHS#111470	30-05-2003 00:00
COMPRESSOR, R&R	19605_UNDER_COMP	Weak	CMPR#34967	31-05-2003 00:00
COMPRESSOR, R&R	17624_UNDER_COMP	Bearing Failure	CMPR#35886	03-06-2003 00:00
EXHAUSTER, R&R	17671_UNDER_EXH	Excessive Dirt - Exterior	EXHS#913870/154	03-06-2003 00:00
TRACTION MOTOR, R&R	10M50469M_BOG2_TM4	Armature Defective/ Earthed	TNCB#302983	04-06-2003 00:00
TRACTION MOTOR, R&R	17635_BOG2_TM4	Ext. Cables /Connections / Boxes Def	TMCB#15D1298	04-06-2003 00:00
TRACTION MOTOR, R&R	10M50469M_BOG2_TM4	Armature Defective	TNCB#302983	04-06-2003 00:00
TRACTION MOTOR, R&R	13542_BOG2_TM3	Armature Defective		05-06-2003 00:00
TRACTION MOTOR, R&R	13542_BOG2_TM3	Armature Defective/ Earthed		05-06-2003 00:00
TRACTION MOTOR, R&R	10M50469M_BOG2_TM3	Arc Horn Flashed / Burnt / Broken	TMCB#303070	06-06-2003 00:00
TRACTION MOTOR, R&R	17651_BOG2_TM3	Armature Defective/ Earthed	TMCB#15D1487	06-06-2003 00:00
TRACTION MOTOR, R&R	17651_BOG2_TM3	Armature Defective	TMCB#15D1487	06-06-2003 00:00
MA/MG, R&R	13193_UNDER_AUX_SUPPLY	Test / Examination	MALT#15D2080	09-06-2003 00:00
TRACTION MOTOR, R&R	10M51518M_BOG1_TM2	Armature Defective	TMOS#262040	11-06-2003 00:00
TRACTION MOTOR, R&R	10M51518M_BOG2_TM4	Armature Defective	TMOS#262065	11-06-2003 00:00
TRACTION MOTOR, R&R	10M51518M_BOG1_TM2	Armature Defective/ Earthed	TMOS#262040	11-06-2003 00:00
TRACTION MOTOR, R&R	10M51518M_BOG1_TM1	Armature Defective	TMOS#262590	11-06-2003 00:00
TRACTION MOTOR, R&R	10M51518M_BOG1_TM1	Armature Defective/ Earthed	TMOS#262590	11-06-2003 00:00
TRACTION MOTOR, R&R	10M51518M_BOG2_TM4	Armature Defective/ Earthed	TMOS#262065	11-06-2003 00:00
MA/MG, R&R	10M50468M_UNDER_AUX_SUP	Auxiliary Transformer Defective	MALT#PB762K	11-06-2003 00:00
TRACTION MOTOR, R&R	17651_BOG2_TM4	Int. Cables / Fields / Interpoles Flash	TMCB#15D1343	17-06-2003 00:00
TRACTION MOTOR, R&R	17651_BOG2_TM4	Int. Cables / Fields / Interpoles Def	TMCB#15D1343	17-06-2003 00:00
TRACTION MOTOR, R&R	17651_BOG2_TM3	Int. Cables / Fields / Interpoles Def	TMCB#283594	17-06-2003 00:00
TRACTION MOTOR, R&R	17651_BOG2_TM3	Int. Cables / Fields / Interpoles Flash	TMCB#283594	17-06-2003 00:00
TRACTION MOTOR, R&R	17644_BOG2_TM3	Armature Defective/ Earthed	TMCB#281482	18-06-2003 00:00

Appendix E: Results for Trend Tests and Failure Behaviour Parameters

The steps in applying statistical techniques were discussed in the Methodology chapter and this appendix summarises the trend test results as well as the failure behaviour and parameters.

Results for Trend Tests and Failure Behaviour Parameters

The results for the three MCs are listed in the following three pages, and throughout the following standard is followed:

- Inter arrival times (X_i) are marked in ***bold*** indicate truncated failure observations. These truncated failure observations were added either to the beginning, the end or both ends of the observation period. In most cases the added observation is larger than the original first/last observation point.
- Where no failure data exists, failure behaviour from another MC is taken, e.g.:
  - No data for COMP MC1, data used from COMP MC3
  - No data for TM3 MC2, data used from COMP MC2
- The evaluation of the Laplace Trend Test (LTT) and Lewis-Robinson (L-R) test results are interpreted according to Table 2.1, repeated below for ease of referencing

Value of *u*	**Description**	**Type of theory**
$-2< U_L<-1$, $1< U_L <2$	Grey area, more tests required	Either renewal theory or repairable systems theory
$U_L <-2$	Reliability improvement, data non-homogeneous	Repairable system theory, use NHPP
$U_L >2$	Reliability degradation, data non-homogeneous	Repairable system theory, use NHPP
$-1< U_L <1$	Non-committal, data homogeneous	Renewable theory, use HPP

- The LTT test results are reported in Table 6.7.

Table 6.7: Test results for the Laplace Trend Test for MC1, MC2 and MC3

	SUPPLY	COMP	EXH	TM1	TM2	TM3	TM4
MC1	2.033		1.600	-0.228	0.243	0.700	1.117
MC2	0.834	-0.362	1.354	2.418	0.818		1.364
MC3	-0.412	2.707	3.025	-0.328	0.361	1.730	2.203
Colour Legend		-1<u<1	-2<u<-1, 1<u<2		<-2	>2	

- When no conclusive trend could be found by the LLT and L-R test, then only the Mann-Kendall trend test is used.
- Based on the results from the trend tests, either non-repairable (renewal) or repairable system theories are used, where:
  - Non- repairable/renewal systems are associated with HPP, and conventional analysis techniques are used such as the Weibull distribution

    - Repairable systems are associated and NHPP, and either the Log-Linear or Power law NHPP failure functions are used.
- Trend tests are performed and failure behaviour parameters calculated
- No Power law functions were found to be optimal for any component, and where NHPP are used, only Log-Linear functions will be seen in the results although the tests have been done to fit the data to either Power law or Log-Linear NHPP.

Results for MC1

Motor Coach	MC1	MC1	MC1	MC1	MC1	MC1	MC1
Component	SUPPLY	COMP	EXH	TM1	TM2	TM3	TM4
Inter-arrival times (X_i)	2571.7		**396.0**	**806.7**	**806.7**	**806.7**	**867.7**
(***BOLD*** indicates *truncated*	252.8		135.5	142.8	748.8	61.0	2286.8
failure observations)	**733.5**		105.9	594.0	**2244.5**	2794.8	**645.5**
			1096.0	**2256.5**		**137.5**	
			122.2				
			26.9				
			678.9				
			162.0				
			447.5				
			154.5				
			66.0				
			119.0				
Laplace Trend Test	**2.033**		**1.600**	**-0.228**	**0.243**	**0.700**	**1.117**
Lewis Robinson test			**1.428**				**1.467**
Mann-Kendall (MK S-statistic)			-20				-4
STD Deviation	1223.9		317.1	913.9	847.3	1274.7	890.4
Mean	1186.0		292.5	950.0	1266.7	950.0	1266.7
Coeff of variation	1.03		1.08	0.96	0.67	1.34	0.70
MK Confidence Factor			87.40%				83.30%
			No trend				No trend
Failure Model	NHPP		HPP	HPP	HPP	HPP	HPP
Failure Behaviour	**Log Linear**		Weibull	**Weibull**	**Weibull**	**Weibull**	**Weibull**
B /α0	-8.69976		1.062652	0.872486	1.237035	**0.491688**	**1.314011**
η/α1	0.000759		279.9794	1083.868	1603.679	**1312.138**	**1950.916**

Instead of indicating truncated or real failures with a *C* value (C_i=0 for truncated failures and C_i=1 for real failures), the truncated inter-arrival times are shown in **bold**.

Results for MC2

Motor Coach	MC2	MC2	MC2	MC2	MC2	MC2	MC2
Component	SUPPLY	COMP	EXH	TM1	TM2	TM3	TM4
Inter-arrival times (X_i)	1398.5	104.0	1379.0	1706.5	**722.4**		**1844.5**
(***BOLD*** indicates *truncated*	435.0	325.0	586.5	492.0	880.1		1469.0
failure observations)	1691.1	1047.0	62.0	567.0	330.0		
		648.4	1215.9	460.0	1519.0		
		239.6	**385.6**	140.0	349.2		
		1362.0		209.2			
Laplace Trend Test	**0.834**	**-0.362**	**1.354**	**2.418**	**0.818**		**1.364**
Lewis Robinson test			**1.695**				**2.317**
Mann-Kendall (MK S-statistic)			-4				
STD Deviation	657.2	496.3	557.4	569.4	486.2		265.5
Mean	1174.9	621.0	725.8	595.8	760.1		1656.8
Coeff of variation	0.56	0.80	0.77	0.96	0.64		0.16
MK Confidence Factor			75.80%				
			Stable				
Failure Model	HPP	HPP	HPP	NHPP	HPP		HPP
Failure Behaviour	**Weibull**	**Weibull**	Weibull	**Log Linear**	**Weibull**		**Weibull**
B /α0	1.250553	1.081816	**0.662057**	-8.09434	1.518403		5.594382
η/α1	1456.854	702.557	**1022.546**	0.000773	890.6089		1776.94

Instead of indicating truncated or real failures with a C value (C_i=0 for truncated failures and C_i=1 for real failures), the truncated inter-arrival times are shown in **bold**.

Results for MC3

Motor Coach	MC3	MC3	MC3	MC3	MC3	MC3	MC3
Component	SUPPLY	COMP	EXH	TM1	TM2	TM3	TM4
Inter-arrival times (X_i)	**643.4**	**2378.0**	**2369.0**	**479.0**	**479.0**	**881.7**	3418
(***BOLD*** *indicates truncated*	5.0	330.5	179.5	318.7	318.7	433.8	**383**
failure observations)	815.1	117.9	417.9	**3002.3**	492.8	1946.0	
	396.0	7.2	312.0		2212.0	112.0	
	1880.5	141.8	100.0			44.0	
		368.0	10.0			**382.5**	
		392.6	**338.6**				
Laplace Trend Test	-0.412	2.707	3.025	-0.328	0.361	1.730	2.203
Lewis Robinson test						1.590	
Mann-Kendall (MK S-statistic)						-7	
STD Deviation	702.5	826.0	822.3	1505.3	894.4	708.0	2146.1
Mean	748.0	533.7	532.4	1266.7	875.6	633.3	1900.0
Coeff of variation	0.94	1.55	1.54	1.19	1.02	1.12	1.13
MK Confidence Factor						86.40%	
						No trend	
Failure Model	HPP	NHPP	NHPP	HPP	HPP	HPP	NHPP
Failure Behaviour	**Weibull**	**Log Linear**	**Log Linear**	**Weibull**	**Weibull**	**Weibull**	**Log Linear**
B /α0	0.408353	-9.178058	-5.767402	0.733074	1.008155	0.764224	-12.4974
η/α1	956.609	0.00132	0.00050	1441.491	1025.889	644.141	0.00181

Instead of indicating truncated or real failures with a *C* value (C_i=0 for truncated failures and C_i=1 for real failures), the truncated inter-arrival times are shown in **bold**.

Appendix F: Conference Article CIE 2012

In 2012, a conference paper was done for Computers and Industrial Engineering 42 Conference, held in Cape Town. The tile is "Exploring Critical Failure Modes in the Rail Environment and the Consequential Costs of Unplanned Maintenance".

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EXPLORING CRITICAL FAILURE MODES IN THE RAIL ENVIRONMENT AND THE CONSEQUENTIAL COSTS OF UNPLANNED MAINTENANCE

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ABSTRACT

This study explores in-service failure modes for rolling stock in the rail environment, identifies the most critical failures and explores the consequential cost of these failure modes. Rolling stock is maintained according to maintenance plans with a major goal being the prevention of in-service failures, but due to the nature of the equipment not all failures can be prevented. In-service failures normally result in train delays or the cancellations of trains not only disrupting commuter services but also causing financial losses.

The typical failures of rolling stock are analysed using data from the facility maintenance management system. The critical failure modes are identified and classified according to cause, severity, consequence and frequency parameters. A decision model is employed to classify the criticality of the failure modes.

The most prominent critical failure modes are analysed to determine root causes, to conclude the investigation. Areas are identified where the focus of future investigation and planned maintenance will have the most significant impact.

1 INTRODUCTION

In asset intensive organisations, strategic asset management is a key to the success of the organisation. Assets fail because of a number of reasons at random times and intervals, and disruption as a result of these failures has consequential effects that cannot always be quantified. Assets should therefore be maintained and operated to predetermined standards and best practices to minimise the impact of failures.

The concepts of Asset Management and Asset Maintenance are often misunderstood. Asset Management refers to the activities and principles over the whole life cycle of the physical asset, to achieve the stated output [1]. Asset Maintenance is part of Asset Management and refers to the actions to retain an item in, or restore it to a state in which it can perform a required function [1].

In this paper the Western Cape branch of a South African passenger rail company is used as a case study, and in-service failures of rolling stock are explored to determine the contribution of the different failure modes to reliability. Delays of trains not only cause disruption to the service but have a financial implication on the business. The contribution of each failure mode to the overall loss is calculated and a cost model is developed to quantify cancellations and delays as a result of these failures.

The condition and performance of other assets and departments have a significant influence on the performance of the rolling stock. There are a number of interfaces that can be taken into account, such as the wheel-rail interface, the pantograph-overhead interface as well as the human interface. For simplicity these influences are excluded from the scope of this paper.

2 BACKGROUND

In South Africa the passenger rail operator also own the infrastructure, unlike railroads in other countries where there are different asset owners. This should be a benefit to the rail operator but because of an imperfect track record on punctuality, the company has been stigmatised as "unreliable" over the past few years, which had a negative impact on rail passenger numbers. Maintenance of the rolling stock fleet and the prevention of failures have an influence on reliability and punctuality, which can be controlled and managed. The contribution thereof will be discussed further.

The service provided by a rail operator can be rated in terms of many parameters and from different perspectives. One such parameter from the rail passenger point of view is the punctuality of the train service, which is probably the most widely used reliability measure in practice [3]. Reliability from the rail operator point of view can be defined around functionality or ability of the rolling stock to perform its duty, and in this paper more emphasis will be placed on this perspective. Punctuality of a train service is a key performance indicator (KPI) valued highly by the rail passenger [5][6], and for the evaluation of a railway system, objective measures like cancellations, delays and the number of realized connections between trains can be measured [5]. Cancellations and delays are also used as key measures of the reliability by the company in our case study.

Many studies have been done on reliability in the railway industry and the effect thereof on rail passengers. In a study Kingham [6] found that reliability is a key factor that will convince vehicle drivers to switch to public transport. According to Cox et al [7] increased passenger density and overcrowding as a result of delays can contribute to low productivity and efficiency in tired workers. Rietveld [8] examined the unreliability of public transport and the effect thereof on travel time, Olsen and Haugland [4] studied influencing factors on train punctuality while Skuce [9] investigated rail passenger satisfaction in the South African environment. These studies found punctuality to be a main reason why people are not making use train services.

Before examining failures and their consequences, a common frame of reference with regard to the principles of failures and reliability need to be defined. A failure occurs whenever a system or component no longer operates within the expected or designed specification, which includes breakdowns and out-of-specification performance. A general definition for reliability is the probability that an item will perform a required function without failure under stated conditions for a stated period of time [10].

Todinov [11] suggests a theoretical framework that link reliability and losses from failures, and he demonstrates, contrary to conventional reliability analysis, that maximising the reliability of a system does not necessarily minimise the losses from failures. The aim is therefore to optimise reliability by taking all factors into account. If maintenance is effectively planned and executed, reliability can increase that can result in less corrective maintenance (CM) required with more opportunity for preventative maintenance (PM) [12].

The effectiveness of a maintenance plan is a key issue, and Ahren & Parida[13] define Maintenance Performance Indicators (MPIs) as a benchmarking tool to measure effectiveness. A typical application of MPI will be to express CR as a ratio to PM and compare to the industry benchmark of 20%. This ratio can indicate the effectiveness of the maintenance planning that has a direct influence on reliability. Pham and Wang [14] define the effectiveness of maintenance around the concept of "imperfect maintenance" where the degree to which the operating conditions of an item is restored by maintenance.

In the background aspects discussed so far it is argued that reliability and failures are two aspects that are critical and must be managed, that they are related and have an influence on each other. It is important to manage and optimise both as a key for business success but care needs to be taken when doing so.

2.1 Cost Of Maintenance

It was mentioned earlier that asset management has a big influence on the success of the organisation, and part of asset management is the maintenance thereof. In a case study by Ahren & Parida[15] it is mentioned that "*maintenance is one of the largest controllable expenditures for the railway industry, as it can reduce cost and improve equipment effectiveness, reliability and performance*". Unfortunately the maintenance department is not seen as value adding to most organisations and regarded as an expense account, which is a popular target for cost reduction programs [15].

In a study by Cavalcante and Almeida [16] they argue that if the average cost of CM is larger than the cost of PM, then only it will be beneficial to predict a failure as there will be a cost saving. Salonen et al [17] comment in a study that the cost of maintenance can be classified in direct cost, indirect cost and non-realized revenue cost, where the latter refers to the loss of income because of reduced sales, missed deadlines, as well as other related factors. Both authors mainly take into account the direct cost of maintenance associated with a failure, but because of a failure there are second line consequences or a ripple effect that can be quantified as follows:

- the change in perception of the customer and future support willingness
- the indirect cost to the customer
- the cost to the economy
- loss in market opportunity

The most prominent of these effects are included in the cost model in the next section.

A popular maintenance strategy is the PM strategy that is used to increase equipment lifetime, reduce downtime and reduce the risk of failures. In our case study a PM strategy is also used and train sets are scheduled on a time base in order to perform maintenance. In-service failures result in CM which is a reactive maintenance approach, triggered by the unscheduled event of equipment failure [18] that should be avoided. Tsang [20] also points out that the reasons for performing PM are to prevent failure, detect the onset of failure and to discover hidden failure. Higgens [12] agrees with Tsang that failures should be analysed, root causes identified and managed according to the maintenance plan that will reduce the number of instances of CM, and to convert findings of the analysis into PM to prevent failures.

A method to analyse failures and determine the root causes is the Failure Mode and Effects Analysis (FMEA), that is defined as "*a procedure by which each potential failure mode in a system is analysed to determine the results or effects thereof on the system, and to classify each potential failure mode according to its severity*" [10]. It can be expanded to FMECA by including criticality of the failure modes in the analysis.

3 METHODOLOGY

In South Africa the safety criteria for rail operations are governed by the Rail Safety Regulator (RSR) [19]. One requirement of the RSR is that maintenance data must be recorded and maintained. This is one reason why the case study uses a Fleet Maintenance Management System (FMMS) [20] to capture maintenance data, and accurate reports can be extracted by means of GQL (General Query Language).

In this study maintenance reports extracted from the FMMS were manipulated and analysed. From the analysis it was determined which groups of components cause the most in-service failures, and a correlation between the number of failures and the duration of failures were established. Passenger and various other statistics were used to determine:

- the cost of a train delay
- the cost of a train cancellation

These were used to determine the consequential cost of each failure mode.

The critical failure modes were classified according to cause, severity, consequence and frequency, and a decision model is employed to classify the criticality of these failure modes.

4 DATA ANALYSIS

4.1 The effect Of In-Service Failures On Punctuality And Reliability

As discussed in the literature study, punctuality is widely used as a reliability measure. Railroads define their punctuality as the probability that a train will arrive at the final destination within a delay of less than a certain margin. An international margin of 5 minutes is used, however in some countries like Switzerland, Netherlands and France 3 minutes is used. It is important to note that this measure only refers to the arrival at the final destination and intermediate stops are neglected [8].

Table 1: Punctuality Comparison Between Different Rail Operators

Country	Operator	Margin used	Probability of arriving within margin
Switzerland (post 2009)[21]	SBB	3 minutes	95.0%
Germany (Aug 2011)[21]	Deutsche Bahn	5 minutes	93.0%
Austria (Jan-Jun 2011)[21]	OBB	5 minutes	96.5%
United Kingdom (UK) (Jan-Feb 2011)[21]	London Underground	10 minutes	96.4%

Country	Operator	Margin used	Probability of arriving within margin
South Africa, Johannesburg (March 2012)[22]	Bombela Operating Company	3 minutes	98.98%
South Africa, Cape Town(2011)	Case study	5 minutes	84.5%

In Table 1 the punctuality of the company in our case study is compared to other rail operators and it can be seen that the company uses the international norm of 5 minutes, but has room for improvement. There can be many reasons for this and in this paper it is assumed that delays can have an effect on punctuality, whether the delay is as a result of failures or operational in nature. The paper will focus further on in-services failures and explore the effect on cancellations and delays.

It is not within the scope of this paper to determine the root causes of punctuality, but the contribution of in-service failures on punctuality and reliability is significant.

4.2 The Consequence Of In-Service Failures

In the literature background a failure is defined as a system or component which no longer operates within the expected or designed specification. When a failure occurs while the train is in-service, these failures can result in cancellations or delays, and is referred to as in-service failures.

As discussed earlier, cancellations and delays are KPI's used by the company in our case study to measure performance. An in-service failure can cause a cancellation and/or delay, it often happens that the knock-on effect of one failure is catastrophic on the service delivery. The contribution of each department to the overall cancellation and delays were calculated and compared.

4.3 Contribution Of Each Departmental To Cancellations And Delays

Information obtained from the Train Operations department was analysed with a special focus on the contribution of the Rolling Stock department to cancellations and delays. In 2011 there were more than 193 000 train trips and based on this number more than 15% of the trains were delayed (table 1) and 12% cancelled [23].

It was questioned by the researchers whether the number of trains delayed is an accurate enough measure. The reason for questioning this measure was because the duration of delays will be different dependant on the severity and the cause of the delay. It was found however that for 2011 the two measures correlate within 0.2% to 5.5% for the different departments. For the Rolling Stock department the variance was 1.2% and it was concluded that either the number of trains delayed or the duration of delays can be used.

Furthermore it was found that in 2011 the Rolling Stock department was responsible for 24% of train delays (ranked second) and 78% of cancellations (ranked first) [23]. Nearly 25% of the cancellations caused by the Rolling Stock department occurred in-service. The rest of the cancellations were as a result of train sets that were not available for service, mainly due to maintenance and vandalism.

From these figures it is evident that the Rolling Stock department has a large influence on the punctuality and reliability of the train service.

4.4 Trends In Rolling Stock Department

Cancellations and delays caused by the Rolling Stock department since 1998 were investigated. In this section the statistics around cancellations and delays are discussed.

4.4.1 Delays

In the previous section the conclusion was made that either the number of trains delayed or the duration of delays can be used as a delay measurement. In Figure 1**Error! Reference source not found.** historical information on the number of trains delayed (D_{trains}) is compared to the time delayed (D_{time}) [23].

The graphs were superimposed which highlight the following:

- In Figure 1 it is unclear why the trend in delays is upwards. The following factors are presented as contributing factors:
    - The trains are becoming older and the majority of the fleet of 406 trains were built between 1958 and 1985. Typical problems are that parts fail more often, lead times are longer, the number of suppliers are limited and spare parts are more difficult to obtain.
    - Business processes are inefficient and outdated.
    - Loss of technical expertise
- Also in Figure 1 the trends for both data sets (D_{trains} and D_{time}) display an increasing trend. This is a significant perspective on the data and it implies that if 2011 is compared to 1998, D_{trains} (number of trains delayed) is 5 times more whereas D_{time} (time trains were delayed) is 8 times more. It can be seen that both graphs follow similar fluctuations until 2008, where after D_{time} increase at a faster rate than D_{trains}. This increase can be explained by Figure 2 where the average time of a train delay (D_{time}/D_{trains}) more than doubled from 1998 to 2008.
- While the trends of D_{time} and D_{trains} seem to be exponential, the trend of the average delay per train (D_{time}/D_{trains}) displays a flattening trend (Figure 2) that is a positive sign in that it is starting to normalise. In the opinion of the authors, the reasons contributing are:
    - From 2009 to 2011 D_{time} stayed almost the same while D_{trains} increased with 35%. This can be interpreted as:
        - the number of trains that are delayed is increasing at a faster pace D_{trains}
        - The deduction can also be made that D_{time} is stabilising although still on a upward curve

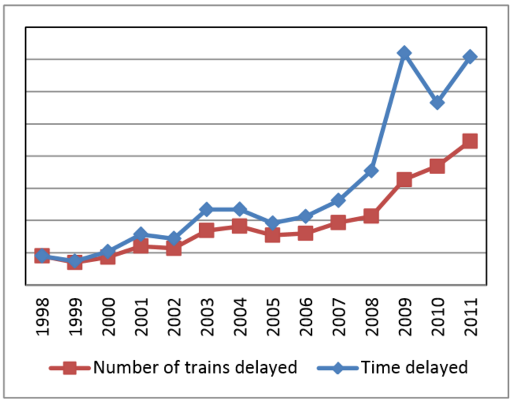

Figure 1: Delays Caused By The Rolling Stock Department Expressed In Number Of Trains Delayed, And In Time Delayed [23]

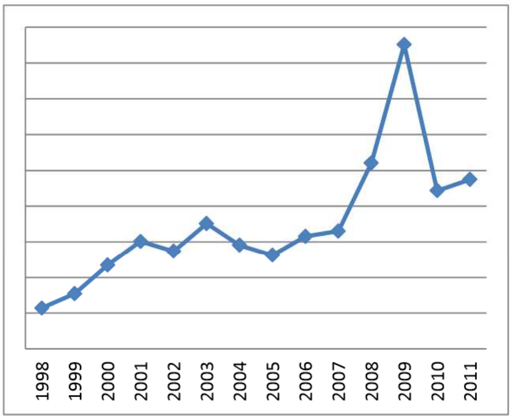

Figure 2: Delay Per Train In Minutes (D_{time}/D_{trains}) [23]

In conclusion it can be noted that delays have increased approximately tenfold compared to a decade ago and should be listed as a KPI for the Rolling Stock department. Delays are more frequent and also becoming longer and should be closely monitored.

4.4.2 Cancellations

The number of cancellations caused by the Rolling Stock department displays an increasing trend as shown in Figure 3 and has increased more than tenfold since 1998. Although this is of concern, not enough information could be obtained to quantify the extent of cancellations. Cancellations are more complex than delays as the unavailability of one train set can result in a number of cancellations which is more difficult to manage.

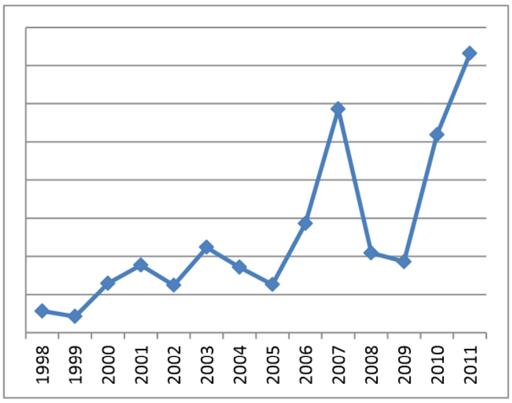

Figure 3: Train Cancellations Caused By The Rolling Stock Department Western Cape [23]

4.5 In-Service Failures For The Rolling Stock Department

4.5.1 In-Service Failure Process Flow

To understand the discussion on the analysis that follows, the in-service failure process flow is presented (refer to Figure 4). When the train driver experiences an in-service failure, the driver reports the failure to the Train Operations Control Centre (TOCC). As a first line maintenance person the driver will evaluate and attempt to resolve the failure, but because of a lack of technical experience or knowledge, it can happen that the driver reports a failure that can be resolved by himself or describe the fault incorrectly. This can result in the improper corrective action being initiated.

After the failure is reported and a job is registered, two parallel, non-related process lines are followed.

1. The failure is attended to by the Failure Department, the reason for the failure noted and the job closed
2. Management investigates the failure and allocates it to the relevant department who will take ownership and responsibility of the consequence of the failure. Taking ownership implies that the cancellations or delays are added to the totals for the department, as described in the previous section.

An analysis was done on in-service failures [24] of 2011 for the region where 85 train sets are running and nearly 1600 in-service failures were experienced. The company grouped the components that fail frequently in component groups (refer to group descriptions in Table 2). Based on the fault codes, the occurrence of each component group was calculated. One of the key drivers of this process is that the correct fault code must be generated before the job is closed and it must be noted that 29.5% of failures have no fault codes which makes the statistics questionable and not totally reliable, but the results are nevertheless a good indication of trends.

4.5.2 Contribution And Frequency Of Component Groups To In-Service Failures

The contribution of each component group was calculated in terms of cancellations and delays, and the results are summarised in Table 2.

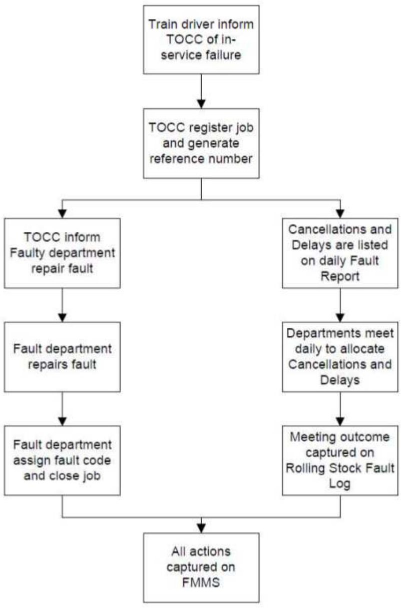

Figure 4 : In-Service Failure Process Flow

Table 2 : Contribution Of Each Component Group On Cancellations And Delays [24]

Group	Group description	Contribution to delays based on time (D_{time}) Column I	Contribution to delays, based on # trains (D_{trains}) Column II	Time per delay Column III	Time per event Column IV	Contribution to Cancellations Column V
E	Electronic Control Equipment	47%	48%	18.0 min	44.3min	31%
P	High Voltage and switch equipment	23%	23%	18.4 min	50.4 min	30%
M	Traction/Auxiliary machine and controls	14%	14%	19.3 min	52.2 min	13%
O	Brake gear	2%	2%	17.5 min	29.7 min	5%
B	Cab and Saloon doors	6%	5%	21.1 min	46.5 min	6%
A	Air related	4%	5%	18.1 min	58.6 min	4%
G	Pantograph	3%	3%	18.9 min	54.0 min	7%
	Other components	1%	2%	13.9 min	20.5 min	4%
				18 min ave	**46 min ave**	

Explanation of Table 2:

- 85% of the number of delays (column II) is caused by failures in component groups E, P and M. It can also be seen that these 3 groups contain all the electronic and electrical components, and these components normally follow the bathtub failure curve. This may explain why so many in-service failures are experienced as some components are old, failures cannot always be predicted and the failure happens suddenly.
- Although contributing only 5% to the number of delays, Group B caused the longest average time per delay (column III, 21.1min). It can be contributed to the fact that cab and saloon doors are regarded as safety items by the RSR and must be repaired if not working. Therefore a train will not depart before the doors are fixed.
- Air related failures (group A) contributed also 5% to the number of delays, but took the longest to repair at 58.6min (column IV).
- Between groups E,P and M, group M causes both the longest time per delay (19.3min) and the longest time per event (52.2min), thus the complexity of failures and the severity of failures can be illustrated by this.
- Group A is the most complex failure group to repair although not contributing to a large number of delays or cancellations.

It can be seen that the ratio for the groups based on the time delayed (column I) or based on the number of delays (column II) correlated within 1%. This means that any one of the two ways to express delays can be used.

Detail statistics are as follows:

- 16% of failures were rectified by the driver attributing to 11.7% delays. This implies that the failures which the drivers can fix are small and are fixed quickly.
- 4.2% cancellations are caused by drivers
- If the Pareto principle is applied, 20% of the failures are responsible for 64% of delays measured in time
- Cancellation show a similar trend to that of delays in that the same 3 component groups caused 74% of cancellations

From the analysis it is evident that 3 component groups (E,P and M) cause most of the cancellations and delays. The Traction/Auxiliary machine and controls (Group M) is a critical group to explore further as the consequence and severity of this component group are relatively more than the other groups.

4.6 Cost Of Each Component Group To The Total Cost Of In-Service Failures

The total cost of a cancellation and a delay was calculated, and various sources were used to obtain statistics on:

i. Average number of passengers on a train [25]
ii. Number of passengers who commute to work, who earn a salary [25]
iii. Average number of trains per day [25]
iv. Demographic distribution of the population who use train as a mode of transport [26]
v. Average income per population group [27]
vi. Number of delays and cancellations for Rolling Stock department [25]
vii. Average train fares [27], duration of trips on Metrorail [28] and on a typical bus [29]

There are a number of assumptions in this cost calculation, and there are also a number of cost factors excluded from this calculation such as:

- The direct cost to repair the in-service failure is not taken into account
- The indirect cost to recover for lost production is excluded
- Non-realized revenue were taken into account, except for the second line consequential or ripple effect costs, as defined earlier
- The average number of passengers of a train was used. In peak hour all passengers on the train is assumed to be commuters and there are many more commuters on the train than average, therefore the cost per delay in peak hour is at least an order higher than on average.

Taken the above into account, the average cost of a delay is calculated. If a train is delayed it is assumed that the commuter will lose a portion of his salary. By using statistics i-vi it was calculated that the cost of a delay will be R506 per minute. Considering an average delay of 20 minutes per train, the average cost per delayed train is R10 000.

Using the same statistics, the cost of a cancellation is calculated, but the following is taken into account:

- Revenue lost because of the cancellation
- Direct loss due to higher cost of alternative transport for the passenger
- Lost wages because of longer travel time on the alternative transport
- Lost wages because of time wasted to arrange and waiting for alternative transport

It was concluded that the estimated average cost of a cancellation is R56 175.

With these cost figures, cancellations and delays of each component group can be expressed in monetary terms.

5 CONCLUSION AND RECOMMENDATIONS

In this paper an analysis of in-service failures in a South African passenger rail company has been conducted, and various statistics and ratios considered. Results and trends were obtained and presented without full detail to protect the intellectual property of the company.

The correlation between maintenance, cancellations, delays and punctuality were discussed, and the effect thereof on reliability cannot be ignored. While this article highlights significant statistics on historical information, it should be further investigated to predict future trends. Historical information alone is not suitable as a prediction of future trends, and by using suitable mathematical models future behaviour can be predicted which can result in less in-service faults.

The analysis of the in-service failures displayed noteworthy trends. The most evident trend is that cancellations and delays are increasing over the years. This trend can partly be attributed to ageing trains, emphasising the need for appropriate maintenance strategies for the age of the equipment. The authors are of the opinion that the increasing trend is not fully explained by the ageing trains and it appears as if this study identifies the existence of opportunities for more optimised maintenance.

The findings on the contribution of each component group are significant as it is a skew distribution and the list of top failures stays almost the same every month. It is recommended that the component groups be redefined to focus on more detailed failures, especially the top failure groups. Another suggestion is to change from component groups to functional groupings where a system belongs to a group. Reliability Block Diagrams can be beneficial to determine dependencies between different functional groupings.

There was an inadequate amount of information to do a full analysis on root causes because the information in the maintenance log was incomplete in terms of fault codes. It is recommended that the fault codes be entered on the job cards as a compulsory field, and once the groups are established the root causes can be analysed from these codes.

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Appendix G: Journal Article Submitted to SAIJE

A journal article was submitted, in October 2014, to The South African Journal of Industrial Engineering (SAJIE). By the time of submitting this research work, there was no feedback yet from the journal, and the article is attached. The title of the article is “Quantifying system reliability in rail transportation in an ageing fleet environment”.

QUANTIFYING SYSTEM RELIABILITY IN RAIL TRANSPORTATION IN AN AGEING FLEET ENVIRONMENT

ABSTRACT

In recent years, the management of physical assets has become increasingly important, even more so in asset intensive organisations. This article presents an approach to quantify reliability of rolling stock assets in the rail environment, making use of failure statistics. Failure distributions and interdependency of different systems are used to determine the impact of component failures on the overall system reliability, and it is used to determine the reliability of individual train sets. Recommendations relating to the future planning of maintenance are included in the article.

OPSOMMING

Die bestuur van fisiese bates het in die afgelope tyd al meer belangrik geword, veral in bate intensiewe organisasies. Hierdie artikel stel 'n metode voor wat die betroubaarheid van rollende materiaal bates in die spoor bedryf kwantifiseer deur gebruik te maak van falingstatistiek. Falings verspreidings en interafhanklikheid van stelsels word gebruik om te bepaal wat die invloed is van komponent falings op die betroubaarheid van die totale stelsel. Hierdie benadering word dan gebruik om die betroubaarheid van individuele treinstelle te bepaal. Aanbevelings word ook gemaak hoe om betroubaarheid te gebruik om die beplanning van instandhouding te doen.

1. INTRODUCTION

An effective rail system depends on the seamless integration of a number of complex systems, and if one system fails, the service can be severely affected. Reliability, availability, maintainability and safety (RAMS) are seen as major contributors to the quality of railway service (Figure 1) and are well covered in the European standard EN 50126 [1]. The standard recognises that railway safety and availability are interlinked and regarded as the most important elements, and it can only be achieved if all the reliability and maintainability requirements are achieved. The quality of railway service is not only influenced by the four RAMS elements, but also operations, maintenance and other factors as shown in Figure 1.

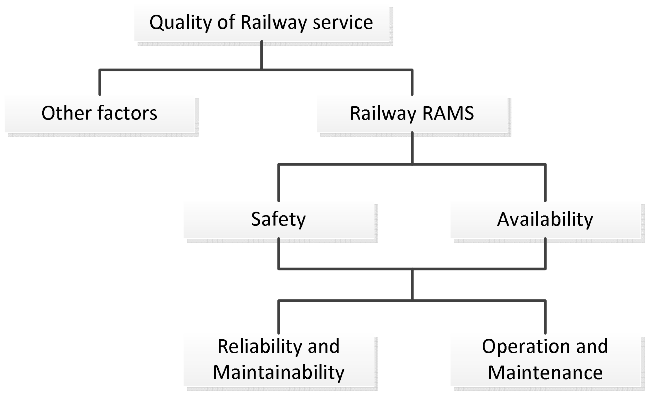

Figure 1: Factors contributing to the quality of a railway service [1].

While all the elements of RAMS are important in the management of railway physical assets, in this article, the focus will be on quantifying the reliability of railway rolling stock and the application of reliability techniques to define a forward looking and leading reliability measure. As a case study, the method is applied using data from a South African rail operator, who operates an aging rolling stock fleet predominantly using time based maintenance. The article also discusses the method used to decide on the maintenance intervals while applying the leading reliability measures.

2. BACKGROUND

2.1 Concept of reliability

The word reliability developed from the word rely, which is defined as a 'sense of dependence or trust and perhaps has a notion to fall back on' [8]. It was first used as early as 1816 by the poet Samuel T Coleridge, who wrote about his friend who inspired everybody around him with 'perfect consistency and absolute reliability' [9]. Since then, the concept of reliability has become rather popular and is used extensively by the general public as well the technical community.

When used by the technical community, the context and interpretation of the word becomes rather specific and can deviate substantially from the popular meaning. There are divergent definitions for reliability but one of the more appropriate and recently used definitions in the context of asset reliability is 'the probability that an item will perform its intended function for a specific interval under stated conditions' [1]. At a first glance, the definition seems to be self-explanatory and misinterpretation appears improbable, but stakeholders need to ensure that the concepts of *intended function*, the duration of the *specific interval* and the scope of *stated conditions* are well understood.

Reliability analysis is a systematic approach to analyse the reliability of systems, identify and access the frequency and causes of failures, and control the consequence of failures [21]. There are many reasons why reliability is important among them reputation, customer satisfaction, operation and maintenance cost, repeat business and for a competitive advantage [20]. But from a maintenance point of view, reliability will contribute to a higher availability which is particularly important in the context of RAMS.

2.2 Reliability, availability and the human factor

As part of RAMS, availability is considered one of the most important reliability performance measures of maintained systems [19]. Availability requires that the item must be 'in a state to perform the required function under given conditions…' [1][42]. The importance of reliability and availability in the rail industry is best described by Milutinovic [42] who quantifies the influence of reliability on availability. Reliability and availability are often misinterpreted and in certain cases erroneously used interchangeably.

Reliability can be grouped into the reliability of equipment and the reliability of people [43]. In EN 50126 [1], the contribution of humans to railway RAMS is acknowledged and more rigorous control of the human factors is called for. Studies have been done on human factors that include the influence of human reliability on systems. Karanikas [43] concluded that human errors contribute to more than three quarters of failures during the life of an asset and stated that 'expecting to achieve perfection from an imperfect human is unrealistic'. Vanderhaegen [44] describes the human behavioural degradation when performing tasks and system degradation due to human actions. Without ignoring the importance of human reliability, in this article, the focus will be primarily on the reliability of equipment regardless of the cause of failure.

As stated, reliability is important but it should not be pursued at any cost. Ultimately, the cost of reliability needs to be weighed against the total combined operation and downtime cost.

2.3 Reliability and maintenance

Maintenance of industrial equipment is defined by Pintelon and Gelders [18] as 'all activities necessary to restore equipment to, or keep it in, a specified operating condition'. The objective of maintenance is to maximise equipment availability by improving the reliability of the system [18] through scheduled preventative maintenance, replacements and inspections (PMRI) [19]. Asset intensive organisations should recognise the importance of an effective maintenance function. However, in many organisations, maintenance is seen as an expense account [17] and not a value adding process able to increase reliability.

Pham and Wang [24] realised that not all maintenance activities improve the condition of an item, and categorise maintenance according to the degree to which the operating conditions of an item is restored. They define the following types of maintenance:

- perfect maintenance - which restores the operating condition of the system to as-good-as-new,
- minimal maintenance - which leaves the condition as-bad-as-old,
- imperfect maintenance - which brings the condition somewhere between the bad-as-old and good-as-new condition,
- worse maintenance - which brings makes the system failure rate or actual age increases without breakdown,
- worst maintenance - which unintentionally causes a failure or breakdown.

Possible causes identified by Pham and Wang [24] for imperfect, worse or worst maintenance include the repair of the wrong part, partial repair of the fault, replacement with faulty parts and human error.

Traditional maintenance practitioners believed that most failures of equipment are age related and a common mistake was to use a single maintenance strategy for all equipment. Failure models are often used to select the most appropriate maintenance strategies, and most of the six traditional failure curves for aging equipment [26] can be managed by periodic time based maintenance activities [28]. Some failures, however, cannot be prevented even by applying the best maintenance strategy, thus, such failures need to be predicted using statistical methods. This approach forms the focus of this article.

2.4 Reliability in the rail context

Many studies have been done on railway reliability and the effect thereof, such as the relationship between reliability and productivity in railroad services [63], the importance of railway reliability to convince drivers of passenger vehicles to switch to public transport [64], the effect of unreliability on travel time [65], overcrowding because of delays and the effect thereof on productivity and efficiency of workers [66] and the effect of reliability on the availability of the service [42]. Railway reliability can be measured in different ways such as the punctuality of the service [63], cancellations and delays [2] and the number of realised connections between trains [2].

From a passenger's perspective, the punctuality of the service is often used as a reliability measure, which is defined as the probability that the train will arrive at the final destination within a certain margin of the scheduled arrival time. The average punctuality of some major European metro railroad operators is around 95% [67] where trains arrive at the final destination within the international margin of five minutes, although some operators use a three minute margin and still manage a punctuality of around 95%. In South Africa, the punctuality of the Metrorail railway system was 84.5% in 2011 [67] based on five minutes, which has room for improvement compared to international benchmarks.

Studies clearly show that reliability is important to railroad companies, thus, the consequence of unreliability cannot be ignored. It is also clear that most reliability measures are based on the performance of the rail service and are lagging indicators, which cannot be related to the source of the unreliability. Lagging indicators show how well the assets were managed whereas leading indicators are forward looking and help manage the performance of an asset [43].

3. MODELLING RELIABILITY

3.1 Systems and theories

Calculating the reliability of a system requires the mathematical modelling of the system in terms of the underlying driving factors. When constant reliability values are used, a snapshot of system reliability is given at a specific time, and when time dependent reliability expressions are used, the system reliability can be observed over a period of time [19].

Systems can be classified as non-repairable or repairable. A non-repairable system is discarded after its first failure [26][46] and modelled using the renewal theory. With the renewal theory, the system is replaced after a failure and the condition restored to the good-as-new condition, and failures are independent and identically distributed (i.i.d.). The renewal theory is not only limited to non-repairable systems because even if a system can physically be repaired (defined as a repairable system), it can still produce failure data that is i.i.d. and can therefore be classified as non-repairable [47].

Normally, a repairable system is not renewed to the good-as-new condition but minimally repaired to the bad-as-old condition by the repair or replacement of the failed component(s) [26]. If the failure data has a trend, the condition of the system can deteriorate (or improve) over time and must be modelled using regression techniques [26]. More about trend testing is discussed later in this article.

The uncertainty associated with reliability can be classified as aleatory or epistemic uncertainty. Epistemic uncertainty represents failures caused by a lack of knowledge of the system and can be represented by mathematical structures such as interval analysis, possibility theory, evidence theory and probability theory [48]. Epistemic uncertainty can be reduced by better understanding the system such as by experimental results or physical models. Aleatory uncertainty is related to randomness and is based on the mathematical structure of probability [48], which is the primary focus of this article.

3.2 Overview of system reliability and RBDs

For more comprehensive insight into the reliability of a system, it is important to be well versed with the configuration of the system and the interaction between the system and its larger domain systems as well as its peer systems, sub-systems and components. Bourouni [21] describes a number of reliability assessment techniques and compares the Reliability Block Diagram (RBD) to other reliability assessment techniques. He describes the RBD as the most logical and natural representation of a system showing how units (components or sub-systems) are logically linked in series, parallel or combinations thereof.

When units are linked in series, the failure of any unit results in system failure, thus, the reliability of a series system is the product of the individual reliabilities, represented by:

$R = \prod_{i=1}^{n} R_i$ (1) where n is the total number of units in the system, R_i is the individual reliability values

Units linked in parallel allow for redundancy and the system remains operational even if only one unit is operational. The reliability of a pure parallel system can be calculated from the individual unreliabilities as shown below.

$R = 1 - \prod_{i=1}^{n} F_i$, (2) where n is the total number of units in the system and F_i represents the individual unreliability of each unit defined as $1\text{-}R_i$.

Unlike a pure series system where the failure of a single unit results in system failure, or where a single unit needs to be operative in a parallel system, there are special variations where the system only operates when a certain number of units are operative in a certain sequence (*k*-out-of-*n system)* [20]. There are three variations of the k-out-of-n system comprising the consecutive-, balanced- and general k-out-of-n system.

In the series configuration, the *consecutive k-out-of-n system* only fails if more than k consecutive units have failed [19]. In a *balanced k-out-of-n system* the failure of one unit can force the shutdown of another unit when in a particular arrangement [19]. In the *general k-out-of-n system*, redundancy can be built into parallel systems where the system is operational when at least k units out of a total n units are operational, and the reliability of the system can be calculated as follows:

$$R = [\sum_{l}(\prod_{i} R_i \prod_{j} F_j)] + \prod_{y=1}^{w} R_y \quad [19]$$

where *l* is the total number of possible combinations,

i : items required to survive

j : items allowed to fail

w : total number of units in the system

The *general case of k-out-of-n systems* is often adequate to model a system and the pure series and parallel systems are special cases of the *general case of k-out-of-n system*. When the system is operational when only one unit is operational, it can be denoted by the *general case of 1-out-of-n system*, which in turn is a pure parallel system. When the system is only operational when all the units are operational, it is a *general case of n-out-of-n systems* simplified by a series system.

3.3 Reliability data and selection of failure distributions

Reliability is considered as the science of failures [21] and the purpose of the reliability engineer is to analyse trends in failure data and determine the Rate of Occurrence of Failures (ROCOF) as accurately as possible. The ROCOF represents the number of failures per unit time. A common erroneous approach used by reliability engineers is to use only the mean time between failures (MTBF) in calculating the ROCOF, ignoring the chronological order of failure events. The result thereof is that an assumption is indirectly made that failures occur randomly over the given period, and the opportunity to model failure trends is lost.

A practical model for the analysis of failure data, modified by Coetzee [49], is shown in Figure 2. It suggests that before a failure distribution can be fitted, failure data should first be tested for a trend and with no trend present, the dependency of failures should be determined. Vlok [31] observes that the test for dependence is most often omitted because a large number of failure observations are required to perform the test with reasonable confidence, and therefore, independence is normally assumed.

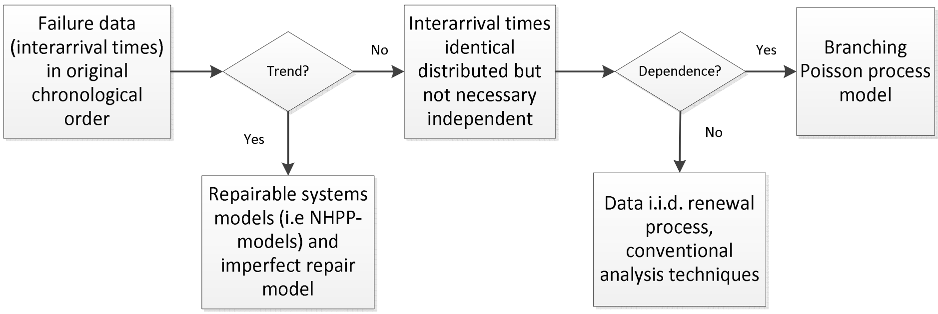

Figure 2: Model identification framework [29,49].

An informal graphical assessment of a trend in failure data is to plot the cumulative number of failures versus the cumulative system operating time. The graph is known as the ROCOF plot [50], and if the ROCOF is constant, the plotted points will roughly be aligned, hence, the times between successive failures are identically distributed (marked 'IID' in Figure 3). If the times between successive failures are decreasing, the curve presents a trend with larger increments in the number of failures per unit time, and the tail end of this curve indicates reliability deterioration (marked 'Deterioration' in Figure 3). Reliability growth is the opposite when the times between successive failures are increasing and the graph concaves down with smaller increments in the number of failures per unit time (marked 'Growth' in Figure 3).

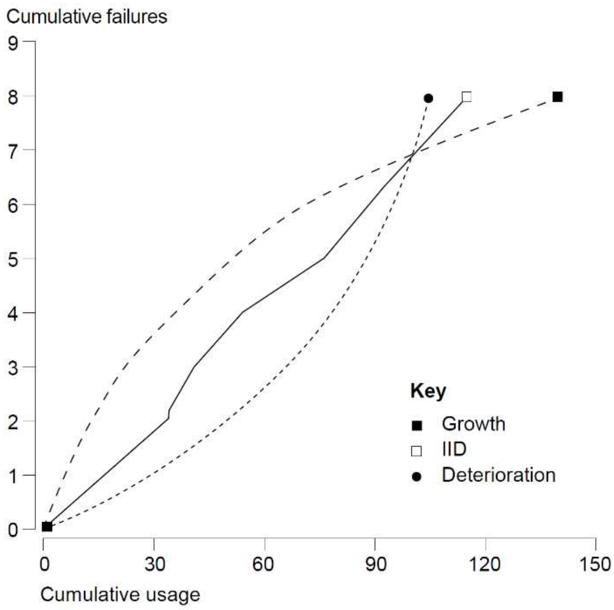

Figure 3: Graphical assessment of a trends in failure data (ROCOF plot [50]).

A simple trend validation can be performed by inspecting the data set using various techniques. The Laplace Trend Test (LTT) [26][31] is the most extensively used test for data sets, and was therefore chosen for this purpose. For failure data which end in a failure, the trend parameter u can be calculated by:

$$u = \frac{\frac{1}{r-1}\sum_{i=1}^{r-1} T_i - \frac{T_r}{2}}{T_r\left[\frac{1}{12(r-1)}\right]^{\frac{1}{2}}}$$

where $T_1, T_2, \ldots, T_r$ = arrival times of failures,

r = total number of observations [26][31]

The null hypothesis (H_0) for the Laplace test is that the distribution of the arrival times corresponds to a Homogeneous Poisson Process (HPP) if the rejection criteria are met [53]. The rejection criteria are based on a standard normal distribution assumption, and will reject H_0 if $u>z_{\alpha/2}$ or $u<-z_{\alpha/2}$ [53]. Based on a typical 95% confidence level (α=5%), H_0 will be rejected if $u>1.96$ or $u<-1.96$, and if $u=0$ it means that the trend is a horizontal line.

Coetzee [26] interprets the value of the Laplace value *u* in Table 1, and from the results the type of theory can be selected. Once the renewable theory or repairable system theory is selected, a family of distributions can be selected and the parameters determined with the most appropriate method.

Table 1: Interpretation of Laplace value U_L [26]

Value of *u*	**Description**	**Type of theory**
-2<u<-1, 1<u<2	Grey area	Either renewal theory or repairable systems theory
u<-2	Reliability improvement, data non-homogeneous	Repairable system theory
u>2	Reliability degradation, data non-homogeneous	Repairable system theory
-1<u<1	Non-committal, data homogeneous	Renewable theory, HPP

When the Laplace *u* value is within the grey area, further tests can be performed. Without discussing in detail the Lewis-Robinson test [53], Mann test [54], Weibull test, Carroll-Hung method [55] can be used to determine whether the data has a trend.

As discussed earlier, systems can be classified into non-repairable and repairable systems. These are discussed in detail in the sections below.

3.3.1 Non-repairable systems

The failure data for a non-repairable system is i.i.d. based on the LTT test, and failures in the data set can be assumed to come from the same statistical distribution, independent from one another. The data is homogeneous, can be represented by various standard distributions and the renewal theory applies. A variety of distributions can be used to model homogenous failure data and the Weibull distribution is one of the most commonly used and flexible lifetime distributions [60], as shown below.

$$f(x) = \frac{\beta}{\eta}\left(\frac{x}{\eta}\right)^{\beta-1} e^{-\left(\frac{x}{\eta}\right)^{\beta}} \quad [26]$$

Substantial research has been done on more effective distributions such as by Unkle and Venkataraman [61], who found synergy between the Weibull and the Army Material Systems Analysis Activity (AMSAA) models. Xie and Lie [62] developed an additive Weibull distribution to represent the bathtub-shaped failure rate data with a single distribution that is related to the exponential and Weibull distributions. For the same purpose, Xie et al [62] developed the new Weibull distribution, and when $\beta<1$, the lifetime data has a bathtub shaped hazard rate function.

Similar to the case of repairable systems, the reliability and related functions can be derived for the Weibull distribution. The exponential distribution, that assumes a constant failure rate, is a special case of the Weibull distribution with $\beta=1$ and $\lambda=1/\eta$. It can be seen that the Weibull model is flexible and can be expanded or simplified. In the Weibull distribution, the β and η parameters can supply valuable information regarding the component in question.

The LTT already confirmed that the life data is independent and identically distributed and the shape parameter (β) can provide an indication whether the hazard rate is increasing ($\beta>1$) or decreasing ($\beta<1$). The η is the characteristic life, which is an indication of the expected life and also of the age at which 63.2% of the components will fail [26].

3.3.2 Repairable systems

When a system is subjected to imperfect maintenance, the system suffers from reliability degradation with an increase in the ROCOF. These are repairable systems, represented by non-homogenous data and can best be modelled by the non-homogeneous Poisson process (NHPP) [26][49][31]. The NHPP is generally suitable for the purpose of modelling data with a trend, relatively easy to use and have been tested fairly well [49]. Two formats of the NHPP found in literature is the log-linear NHPP, represented by

$$p_1(t) = e^{\alpha_0+\alpha_1 t}, \text{ with } -\infty < \alpha_0, \alpha_1 < \infty, t \geq 0 \quad [26][31]$$

and the power law NHPP, represented by

$p_2(t) = \lambda\beta t^{\beta-1}$, where $\lambda, \beta > 0, t \geq 0$. [26][31]

The NHPP repairable systems are best modelled with $\alpha_1 > 0$ (log-linear NHPP) and $\beta > 1$ (power law NHPP), and a linearly increasing failure rate when $\beta = 2$ (power law NHPP) [26]. System reliability, the expected number of failures and MTBF can be calculated from the NHPP models as shown in Table 2.

Table 2: NHPP equations for repairable systems for the interval (T_1,T_2) [26][49][31]

	Log-linear NHPP **with** $-\infty < \alpha_0, \alpha_1 < \infty, T_2 \geq T_1 \geq 0$	**Power law NHPP** **with** $\lambda, \beta > 0, T_2 \geq T_1 \geq 0$
Expected number of failures	$E_1(N(T_2) - N(T_1)) = \frac{1}{\alpha_1}(e^{\alpha_0+\alpha_1 T_2} - e^{\alpha_0+\alpha_1 T_1})$	$E_2(N(T_2) - N(T_1)) = \lambda(T_2^{\beta} - T_1^{\beta})$
Reliability	$R_1(T_1, T_2) = e^{\frac{-(e^{\alpha_0+\alpha_1 T_2} - e^{\alpha_0+\alpha_1 T_1})}{\alpha_1}}$	$R_2(T_1, T_2) = e^{-\lambda(T_2^{\beta} - T_1^{\beta})}$
MTBF	$MTBF_1(T_1, T_2) = \frac{\alpha_1(T_2 - T_1)}{e^{\alpha_0+\alpha_1 T_2} - e^{\alpha_0+\alpha_1 T_1}}$	$MTBF_2(T_1, T_2) = \frac{T_2 - T_1}{\lambda(T_2^{\beta} - T_1^{\beta})}$

The estimation of the parameters from life data can be done using techniques such as the least-squares estimation (LSE) and the maximum likelihood estimation (MLE), and a test such as the Kolmogorov-Smirnov (KS) test can be used to determine the goodness-of-fit. However, this is not the primary purpose of this article and is not discussed further.

4 METHODOLOGY FOR MODELLING RELIABILITY

In the literature review, the importance of measuring and managing reliability is discussed and different methods are discussed to calculate reliability. The methodology followed to calculate the reliability of a system is presented in this section, summarised in Figure 4. It consists of three steps starting with the creation of the model and ends with the interpretation of the results. Each step is discussed in more detail below and applied in the case study.

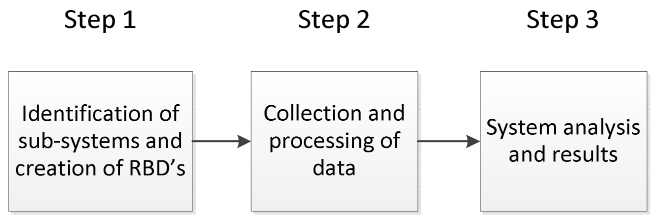

Figure 4: Methodology followed for calculating reliability.

Step 1 : Identification of systems and creating RBD's

The first step is to analyse the system, simplify the systems and identify the important sub-systems. It is important that the contribution of sub-systems towards reliability, their interaction with other sub-systems as well as redundancy be understood. The optimal assignment of components for every sub-system is also important and the sub-systems must be balanced.

Step 2 : Collecting and processing of data

Once the sub-systems and components are identified, the best source of failure data must be identified, data extracted and analysis techniques used to determine relationships within the data sets (data mining). Techniques such as the Laplace trend test is used to search for trends in data sets, and failure distributions are then fitted to the data accordingly. There are various software packages available which can process data easily but Microsoft® Excel was preferred for all the data processing

Step 3 : System analysis and results

Once the interaction of sub-systems is known, RBD's are created and failure distributions determined for the components. The system can then be analysed. Again, Microsoft® Excel was used to simulate the performance of the system over a period of time, and the contribution of components and sub-systems to system reliability could be identified.

5 CASE STUDY

The methodology is discussed in the previous section and it is demonstrated by means of a case study where the reliability of rolling stock at Metrorail (a subsidiary of the Passenger Rail Service of South Africa (PRASA)) was modelled. Metrorail operates an aging fleet of trains, some in operation since 1958, and they predominantly use of cancellations and delays as a reliability measure for their fleet [67].

5.1 Train set configuration

Metrorail defines a Motor Coach (MC) as a powered rail vehicle able to pull unpowered passenger trailers (PT) and also able to transport passengers. A typical Metrorail train set consists of nine PTs and three MCs, with one MC in the middle and at both ends of the train set. The contribution of PTs towards the reliability of a train set is insignificant compared to the contribution of the MCs, therefore, for the purpose of this article, the train set is represented by three MCs only.

A MC consists of various sub-systems, configured in series and parallel. Although the sub-systems are constituted of several components, a basic model was constructed demonstrating the interaction of four different sub-systems (refer to Table 3). Although a risk analysis based on the impact and probability of occurrence, would have been more effective in identifying the components within each sub-system, the approach in this study is to construct a basic model where each sub-system is represented by a single component. The reasons why these components are specifically selected for the MC model are:

- each component is the main component in the respective sub-system
- the components are either an electric motor or driven by an electric motor
- these components combined contribute to more than 60% of cancellations and delays of rolling stock at Metrorail [67].
- these components are serialised, repaired by Metrorail and failure data is available

5.2 RBD Models

The details of the selected components are listed in Table 3 and the number of components required to survive in either a MC or a train set is indicated. The RBD of a MC is shown in Figure 5, which shows the inter relationship of the components and the redundancy.

Table 3: Description of main components and systems of a MC.

			Number required to survive	
Sub-system	**Represented by**	**Abbreviation**	**MC**	**Train set**
Power generation	Auxiliary power supply generator	AUX	1/1	2/3
Compressed air	Compressor	COMP	1/1	2/3
Vacuum system	Vacuum exhauster	VE	1/1	2/3
Propulsion system	Traction motor	TM	2/4	6/12

Most of the components are connected in series on a MC with redundancy only in the traction motors (TMs). The TMs are best described by a *balanced k-out-of-n* system represented by a series-parallel system, where each bogie on the MC is represented by two TMs in series. A MC needs to have at least two TMs operating in series, which means that the failure of one TM will shut down the other TM on the same bogie.

By making use of equations (1), (2) and with individual reliabilities for each component, the reliability of the TM sub-system can be calculated as follows:

$$R = 1 - \prod_{i=1}^{n} (1 - \prod_{j=1}^{m} R_i)$$
$$= 1 - \prod_{i=1}^{2} (1 - \prod_{j=1}^{2} R_i)$$
$$= 1 - (1 - R_1 R_2)(1 - R_3 R_4)$$

where R=Reliability, R_1=Reliability of TM1, R_2 = Reliability of TM2, etc.

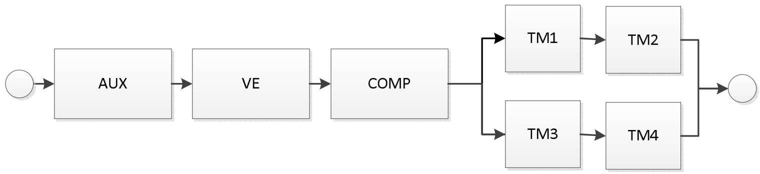

Figure 5: Simplified RBD for a MC.

The RBD for a train set, consisting of 3 MCs, is shown in Figure 6. It can be seen that more redundancy is present in this configuration compared to a single MC. The power generation, vacuum and compressed air systems are best described by k-out-of-n systems, where two out of three sub-systems are required to be operational for the system to be functional.

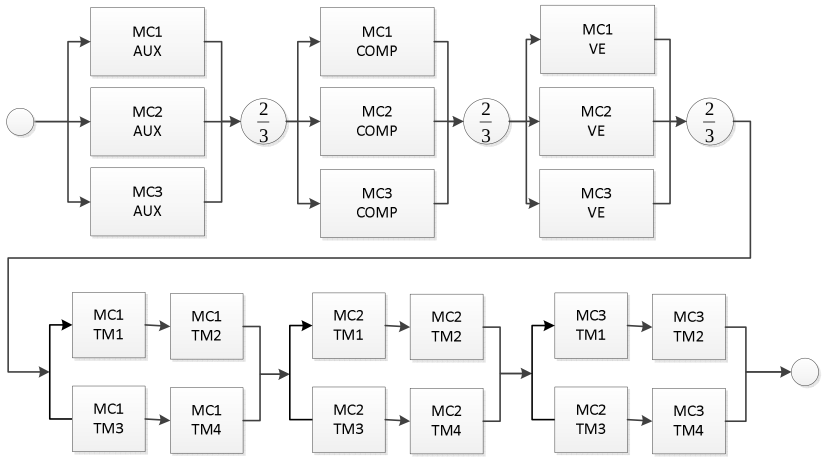

Figure 6: Simplified RBD for a 3MC train set.

5.3 Collecting and processing of data

Once the logic of the sub-systems is understood and a RBD constructed, the failure characteristics of the different components can be calculated. Failure data from 2004 until 2013 was used from Metrorail's FMMS (Facility Maintenance Management System) to determine life distributions and the data represents nearly 200 MCs of the 5M type train. It was reported by Metrorail that the data is not complete as the FMMS was not operating at times, thus, the assumption is made that the available data represents the real situation. For the purpose of this article, three MCs were selected with the worst failure data during the observation period.

For simplicity, failure data was limited to the replacement of components only, i.e. perfect maintenance, ignoring any maintenance done in between the replacements. All components have one or more truncated failure observations (also called suspensions), where the last failure data points of the data set are not failures but merely, the end or beginning of the observation period.

The ROCOF graph for the exhauster of MC3 is shown in Figure 7. Three distinct periods are visible:

- Point 1 to 3, where reliability growth can be observed
- Point 3 to 5, deterioration period
- Point 5 to 7, reliability growth

The *u* factor for the LTT was calculated as 3.03, which indicates a strong overall reliability degradation trend over the observation period. So, although it seemed like the three periods were predominantly reliability growth periods, it is important to validate the data by performing trend tests.

The LTT is performed on the components of the three selected MCs and where the LTT results were in the grey area, the Lewis Robinson and Mann tests were used. The same methodology is followed for all the MCs, but for simplicity only, the results for MC3 are reported in Table 4.

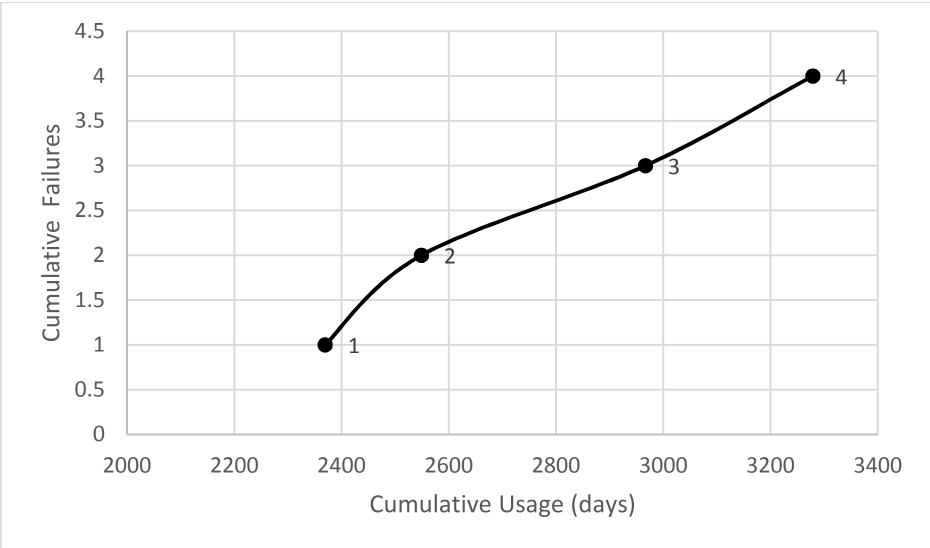

Figure 7: Failure data plot for MC3 exhauster.

It can be seen that the compressor, vacuum exhauster and traction motor 4 have reliability degradation trends. By using the LSE method, the data was fitted to either the power law NHPP or the log linear NHPP function. The LLT result were non-committal for the auxiliary equipment, traction motor 1 and traction motor 2. For these equipment, the renewable theory HPP was followed and the failure data fit to the Weibull distribution using the linear regression method. The LTT results for the traction motor 3 was in the grey area and the Lewis Robinson test was no more conclusive (U=1.55). Furthermore, with the Mann test, it was found that there was no trend (Mann Kendall Statistic=-7, Coefficient of Variation=1.12). It was, therefore, concluded that the HPP with the Weibull distribution will be the best fit, and the Weibull parameters calculated using the LSE (η=644.1, □=0.764).

Table 4: Failure distribution parameters for the main components of MC3.

Component	**LLT**	**LTT implication**	**Failure Behavior**	**Parameters**	
AUX	-0.41	Non-committal	Weibull	η=956.6	□=0.408
COMP	2.71	Reliability Degradation	Log Linear NHPP	α_0=-8.1975	α_0=0.00086
VE	3.03	Reliability Degradation	Log Linear NHPP	α_0=-8.9519	α_0=0.00112
TM1	-0.33	Non-committal	Weibull	η=1441.5	□=0.733
TM2	0.15	Non-committal	Weibull	η=876.5	□=1.046
TM3	1.73	Grey area	Additional tests required		
TM4	2.20	Reliability Degradation	Log Linear NHPP	α_0=-12.4974	α_0=0.00181

For each component, the KS test was used to determine the goodness-of-fit. The null hypothesis of the KS test states that the data follow the specified distribution, and it was rejected when the KS statistic (D_n) was greater than the critical value for the KS test (based on a confidence level of 90%).

6 DISCUSSION OF RESULTS

An analysis was done for three individual MCs and a train set, made up from the three MCs. The results and a comparison of the reliabilities are reported in Figure 8. It becomes clear that the reliability of MC2 and MC3 follows a similar trend, with MC1 initially higher than MC2 and MC3 but then reducing to be significantly less reliable than MC2 and MC3.

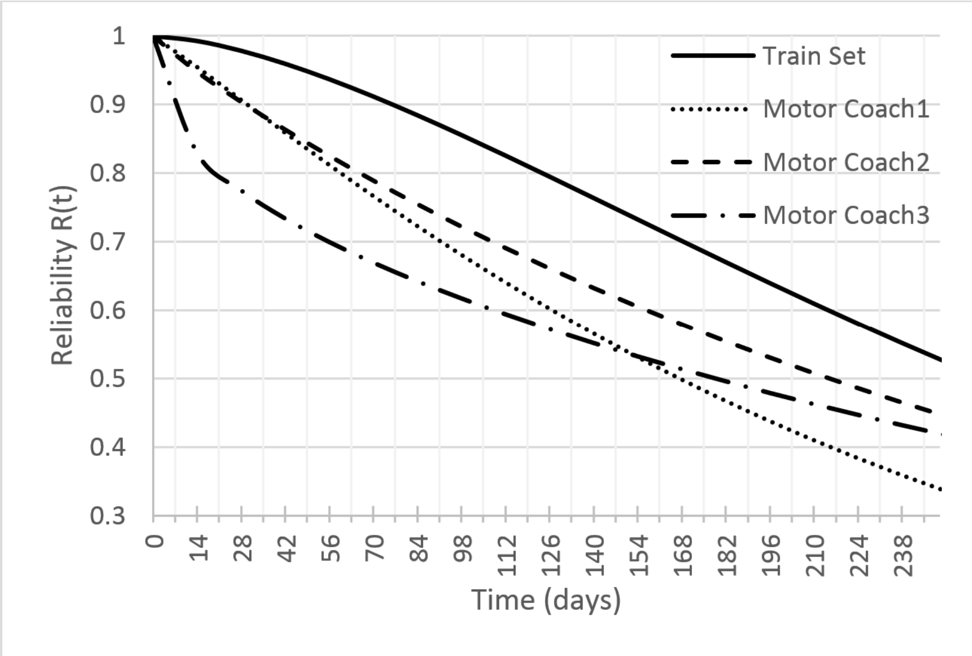

Figure 8: Reliability of a train set and the individual reliabilities of MCs.

From the plot in Figure 8, the time period for a reliable life (also called warranty time) can be derived. Because of redundancy in the MCs, the reliability of the train set is higher than the reliability of any of the individual MCs. For example, the warranty time for the MCs over 14 days are 95.5% for MC1, 94.8% for MC2 and 83.0% for MC3. The overall warranty time for the train set is 99.3% over 14 days, which is higher than any of the individual reliabilities of the MCs. This, however, shows that this train set can only guarantee 99.3% reliability over a 14 day period, which can have an impact on punctuality, cancellations and delays.

The reliability of MC3 shows an initial sharp decline. In Figure 9, the sub-systems of MC3 are shown and it can be clearly seen that the auxiliary equipment has a significantly lower reliability than the other sub-systems. It follows a Weibull distribution with η=956.6 and □=0.408 and with such a low □ value, the steep reliability degradation can be expected.

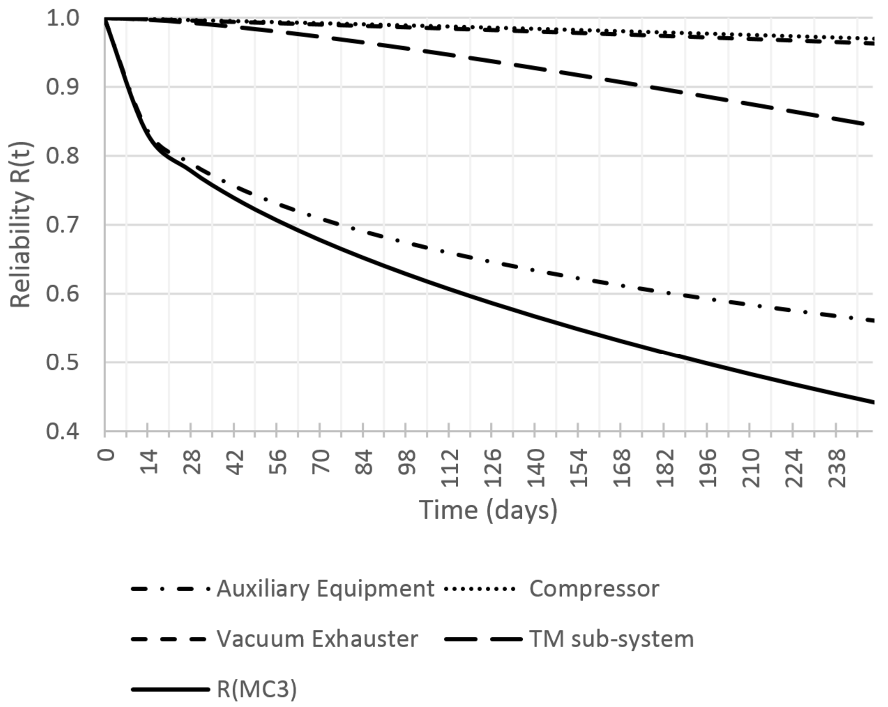

Figure 9: Reliability of the individual sub-systems compared to the reliability of MC3.

At Metrorail, the train sets are maintained every 14 days, and both the maintenance and operations departments expect a high level of reliability during the 14 day cycle. The train operations department, who operates the train sets, can quantify their expected reliability in terms of the percentage successful missions completed, where a successful mission is defined as a train run without failure.

This percentage successful missions can be used by the maintenance department as a reliability target, and by using the reliability model as described in this article, the reliability of the train sets can be quantified based on failure statistics and compared to the reliability target.

7 CONCLUSION

Based on the results presented in this article, it can be concluded that system reliability for rolling stock in the rail environment can successfully be quantified. This reliability measure is a leading indicator and the source of unreliability can be identified. Based on lifetime data and the interdependence of different systems, the overall reliability and the contribution of each component on the entire system can be calculated. It is also shown how time dependent reliability expressions are used to study the reliability over the life of the system.

Instead of using time based maintenance, maintenance schedules can now be created based on the reliability of individual train sets. Train sets that meet the reliability target can be scheduled for maintenance less frequently than train sets that do not meet the target. This will not only increase the availability of train sets but also refocus the efforts of the maintenance department on the less reliable train sets. This provides a different approach to maintenance management for aging rolling stock fleets, which, and with the abundance of failure statistics, can contribute to RAMS in rolling stock.

8. FUNDING

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